

EXHIBIT 1

REDACTED

EXHIBIT FILED UNDER SEAL

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**UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA**

ERICA FRASCO, individually and on behalf of
all others similarly situated,

Plaintiff,

v.

FLO HEALTH, INC., GOOGLE, LLC,
FACEBOOK, INC., APPSFLYER, INC., and
FLURRY, INC.,

Defendants.

Case No.: 3:21-cv-00757-JD

EXPERT REPORT OF JENNIFER GOLBECK

May 9, 2023

Pursuant to 28 U.S.C. § 1746, I Jennifer Golbeck, hereby declare and state as follows:

I. INTRODUCTION AND SUMMARY

I, Jennifer Golbeck Ph.D., am a professor in the College of Information Studies, and director of the Social Intelligence Lab at the University of Maryland. I am an expert on machine learning systems, and I have researched and written extensively about social media companies.

The materials I have considered when forming my opinions are cited herein. Plaintiffs are paying a rate of \$795 per hour for my services, of which I personally receive approximately \$550. My compensation is in no way contingent on the outcome of this case. My qualifications are described in Section II, below.

I have been asked to opine on whether Meta used, in any of its machine learning systems, data related to Flo Health App users ("Flo App User Data") received through the Facebook SDK, for purposes other than providing analytics and advertising to Flo Health. [REDACTED]

I have been asked to opine on whether Google used, in any of its machine learning systems, Flo App User Data received through its SDKs (including the Google Analytics for Firebase SDK ("GA4F")), for purposes other than providing analytics and advertising to Flo Health. I conclude Google did use that data in its advertising business for purposes other than providing analytics and advertising to Flo Health.

My opinions as to Meta and Google are independent of each other though this Report should be read in its entirety, as concepts (*e.g.*, concepts related to machine learning) may be thoroughly explained in one section and then merely explained by reference in a later section.

I reserve the right to amend this report, including to reflect new information that becomes available to me in light of the discovery process and/or future rulings from the Court.

Summary of Conclusions Regarding Meta. [REDACTED]

1 [REDACTED]
2 [REDACTED]
3 [REDACTED]
4 [REDACTED]
5 [REDACTED]
6 [REDACTED]
7 [REDACTED]

8 Machine learning refers to processes whereby computers are provided data and a goal, and
9 computer operations generate a predictive model. Machine learning systems are generally different
10 from human-made predictive models in several ways. The size and complexity of machine learning
11 generated models generally make it practically impossible to reconstruct an intuitive explanation of
12 why the model works. Especially in the sort of large-scale systems [REDACTED] it is generally
13 accepted that it is not feasible to provide meaningful explanations of *why* the system made a
14 specific prediction, even though the system is predictively useful.

15 Relatedly, the ability of computers to construct models based on vast quantities of data
16 generally means that all data made available to the system could be useful. Whereas a human might
17 consider various intuitively plausible inputs to construct a formula to predict, for example, beach
18 attendance (*e.g.*, temperature, season, water quality), a machine learning system can derive
19 predictively useful information from an arbitrarily large number of data points and does not depend
20 on any intuitive explanation of why a specific datapoint is predictively useful.

21 As a result, it is generally understood that (1) the more data a machine learning system has
22 access to, the more powerful it will be and (2) it is not productive, *ex ante*, to make guesses
23 regarding which additional data will most increase the predictive power of a machine learning
24 system. As a result, those designing or utilizing machine learning systems generally do not make *ex*
25 *ante* determinations of which data is useful, and instead provide the system with as much data as
26 possible, given the available constraints (*e.g.*, the cost of storing data and training models).

1 Additionally, because a machine learning system constructs its predictive model from all
2 data made available, all the data made available is necessarily used by that system, regardless of
3 what degree of predictive weight a resulting model places on any given data point. In other words,
4 the act of developing a predictive model is a critically important step in any system dependent on
5 machine learning, and the use of the data in developing that model is a correspondingly important,
6 valuable use of that data, regardless of whether the ultimate model places much weight on any given
7 data point. As just explained, this is true because the training process is itself an important part of
8 the overall system. It is also true because even data that is ultimately given little (or even no)
9 weight in a particular model, necessarily played a role in the statistical process used to generate that
10 model.

11 Furthermore, once a model has been generated (*i.e.*, “trained”), the actual predictive value of
12 any given piece of information cannot be intuitively described, as the model as a whole functions to
13 produce useful predictions and does so in a way that is not susceptible to intuitive explanation. As
14 such, it is reasonable to state that all data available to that model in operation is used by that model,
15 and it is not usually feasible (and not part of the usual parlance of those working with machine
16 learning) to discuss the relationship between a particular piece of data and the predictions made by
17 the model. [REDACTED]

18 [REDACTED]
19 [REDACTED]
20 [REDACTED]
21 [REDACTED]
22 [REDACTED]
23 [REDACTED]
24 [REDACTED]
25 [REDACTED]

26 **Summary of Conclusions Regarding Google.** Google also derives most of its revenue
27 from advertising and uses machine learning systems in the operation of its advertising business. It

1 received Flo App User Data through the GA4F SDK and that data was made available to Google's
 2 machine learning systems used in the Google Analytics for Firebase product. Due to Flo linking its
 3 GA4F SDK account with Google Ads, the data was also made available to Google Ads. As a result,
 4 Google's machine learning systems were given access to the Flo App User Data for the training and
 5 operation of machine learning models. These models could be used by Google to service
 6 advertisers, including advertisers other than Flo. It is my opinion that Google used the Flo App
 7 User Data it received in Google's advertising business.

8 **II. QUALIFICATIONS**

9 I hold bachelor's and master's degrees in computer science from the University of Chicago
 10 and a Ph.D. in computer science from the University of Maryland. I am a professor in the College
 11 of Information Studies at the University of Maryland, where I teach classes on data science, data
 12 analytics, and social networks, among other topics.

13 I have authored multiple books and over 200 refereed articles on social networks and
 14 machine learning systems. I have spoken and presented research on these topics at dozens of top-
 15 tier academic conferences and have spoken as an expert on these topics in other public venues, such
 16 as delivering speeches on these topics at TEDx events.

17 I have received many awards from reputable organizations for my scholarship on social
 18 networks and machine learning systems. I am routinely interviewed as an expert on these subjects
 19 in news media articles, internet publications, and podcasts.

20 I have worked extensively with machine learning systems, including developing machine
 21 learning projects, initializing the training of models, and using models trained by machine learning
 22 in various applications.

23 I have testified as an expert in the following cases: *USC IP Partnership, L.P. v. Facebook,*
 24 *Inc.*, No. 6:20-cv-00555-ADA (W.D. Tex.); *Comcast Cable Communications, LLC v. OpenTV, Inc.*,
 25 No. 3:16-cv-06180-WHA (N.D. Cal.); *Jensen v. Cablevision Systems Corp.*, No. 2:17-cv-00100-
 26 *ADS-AKT*, (E.D.N.Y); *PGH Global (Cayman) Ltd. v. Liquid Interactive LLC*, No. 5:2017-cv-
 27 *00454*, (E.D. Pa.); *Blue Calypso, Inc. v. Groupon, Inc.*, No. 6:12-cv-00486, (E.D. Tex.); *Campbell*
 28

1 *v. Facebook Inc.*, No. 4:13-cv-05996, (N.D. Cal.); *SEC v. City Capital Corp.*, No. 1:12-cv-01249,
 2 (N.D. Ga.); *Rembrandt Social Media, LP v. Facebook, Inc.*, No. 1:13-cv-00158-TSE-TRJ, (E.D.
 3 Va.); *Daou v. Huffington*, No. 651997/2010, (N.Y. Sup. Ct., New York County).

4 My qualifications are further detailed in my curriculum vitae, which is attached as
 5 **Appendix A.**

6 **III. BACKGROUND**

7 **A. Background Concerning Flo and Flo’s Use of SDKs**

8 Flo Health Inc. (“Flo”) is a company that owns and operates the Flo Health App. Flo
 9 describes the Flo Health App as the “#1 period and ovulation tracked worldwide” and states it is
 10 used by over “250 million people around the globe . . . as their ovulation and period tracker app,
 11 fertility calendar, and pregnancy assistant.”¹

12 As discussed herein, Flo used SDKs released by Meta and Google, which were implemented
 13 within the Flo Health App and resulted in data being transferred to Meta and Google. Meta and
 14 Google received data related to Flo App Users’ interactions with Flo and within the Flo Health App.

15 The data Meta and Google received through these SDKs can be classified into two
 16 categories. First, there is data associated with “Standard App Events,” which refer to user
 17 interactions of a type that is predefined by the SDK operator (*e.g.*, Meta or Google), such as
 18 downloading the application or opening the application. Thus, “Standard App Event Data” refers to
 19 data an SDK operator (*e.g.*, Meta or Google) receives through an SDK due to the occurrence of a
 20 Standard App Event. Second, “Custom App Events” are defined by the application developer (here,
 21 Flo) and can contain nearly any information, such as what the user wrote in a field or selected in a
 22 survey. Thus, “Custom App Event Data” refers to the data the SDK operator (*e.g.*, Meta or Google)
 23 receives through an SDK due to the occurrence of a Custom App Event. For example, when an
 24 application user types out a response to a question asked by the application, if the application
 25 developer has configured their application to do so, the Custom App Event title and the user’s
 26 response will be received by Meta and/or Google.

27
 28 ¹ Flo, *Homepage*, <https://flo.health> (last visited May 7, 2023).

1 The data received by Meta and Google related to Custom App Events included data related
 2 to Flo Health App Users' interactions on the Flo Health App [REDACTED]
 3 [REDACTED].² As used herein, the terms "Flo Standard App Event
 4 Data" and "Flo Custom App Event Data" respectively refer to Standard App Event Data and
 5 Custom App Event Data related to interactions on the Flo Heath App.

6 **B. Background Concerning Machine Learning**

7 As noted above, one use of data is to train and operate a machine learning system to
 8 accomplish a given result. For example, as discussed herein, [REDACTED]

9 [REDACTED] Machine learning algorithms describe processes by
 10 which a computer can analyze data and build a model.³ The defining trait of machine learning is
 11 that the computer system itself determines how best to make predictions based on training data,
 12 rather than a human assigning weights to potentially relevant input data.⁴

13 A machine learning system is given access to data which includes a result one wants to
 14 predict, and the system determines how best to weight the data to make the desired prediction.⁵
 15 That process is called "training," and the result is referred to as a "model."⁶ If one wants to make a
 16 prediction, where the result is not known, the model can be used to do so.

17 For example, suppose you want to predict which people are most likely to click an ad for
 18 maternity clothes. Imagine that you have data on which people previously clicked or did not click
 19 on the ad, as well as data about those people. The additional data could include some fields with an
 20 obvious meaning, like a field labeled "sex" with corresponding data, "male" or "female." However,
 21 the data may also include fields with no obvious meaning, like a field labeled "App Event 7F3AB9"
 22 with corresponding data values of 1 or 0; that field may represent the answer to some unknown
 23 survey question and values of "yes" or "no," or it may not — you do not know.

24
 25 ² FLO-00001891-99; META-FRASCO-0000001167; Exhibit C to Google's Fourth Supplemental
 26 Responses to Plaintiffs' Interrogatories, Set One.

27 ³Ethem Alpaydin, *Introduction to Machine Learning* (MIT Press, 2020).

28 ⁴ *Id.*

⁵ *Id.*

⁶ *Id.*

Clicked on ad for maternity clothes?	App Event 7F3AB9	Age	Sex	Income
Yes	1	45	Female	\$51,000
Yes	1	20	Female	\$61,000
Yes	0	23	Male	\$33,000
Yes	1	50	Female	\$130,000
No	0	31	Male	\$19,000
No	0	18	Male	\$44,000
No	1	40	Female	\$80,000
No	0	32	Male	\$51,000

A machine learning system could build a model from data like this to predict whether other people are likely to click the advertisement, by essentially looking at correlations in the data set suggesting whether people — with similar values in the last 4 columns — clicked the ad.

In common machine learning terminology, a system that assesses whether people will be in one group or another — *e.g.*, those who click the ad and those who do not — is called a “*classification machine learning algorithm*,” because it sorts (or classifies) into categories.⁷ In the common vocabulary used to discuss such systems, each row in the table above represents one “instance” (of the set of data collected), each type of data used to make the prediction (columns 2-5) are called “features” (here, “App Event 7F3AB9,” “Age,” “Sex,” and “Income”), and the category the instances are sorted into (here, whether the person clicked the ad) is called the “class.”⁸ Since there is “ground truth” (*i.e.*, known examples where the person clicked the advertisement or did not) for each instance in the table above, the system can use correlations within that data to test what model is most accurate at predicting what class a given instance belongs to.⁹ The process by which a machine learning system builds a model is called *training*, because the system “learns” the patterns in the data to create the predictive model. A trained model can produce predictions based on new instances, where feature data is available for that instance, but where the class is not yet known, *e.g.*, if the person will click the ad.

⁷ *Id.*

⁸ *Id.*

⁹ *Id.*

1 A human might begin by looking at data points they expect to be predictive. For example,
2 the person may guess that a person's sex and income will predict their likelihood to look at a
3 maternity advertisement and test that concept with statistics to develop a model. As discussed
4 below, machine learning systems approach this task differently.

5 A machine learning system will consider the data and similarly construct a model.
6 However, relative to the human, a machine learning system can consider a near limitless number of
7 models using a near limitless amount of data. In this way, a machine learning system is
8 qualitatively different from most human-driven modeling processes because the scale of the
9 system's statistical capabilities means it does not need to begin with hypothesizing which data
10 might be most predictive, as it can usefully weigh all available data.

11 Therefore, while human-designed predictive models often begin with intuitions about the
12 likely meaning and significance of data, a machine learning system does not proceed in that way.
13 One result of the common human-designed modeling approach, which begins with intuitions, is that
14 a human often begins modeling by trying to understand what the various data points mean or
15 represent. Continuing with the prior maternity clothing advertisement example, a human looking at
16 a data set that includes a column labeled "sex" and rows underneath it stating "male" or "female,"
17 may reasonably conclude that they have data about the sex of the users and guess that this data may
18 be predictively useful, test that prediction with statistics, and incorporate it into their proposed
19 predictive model. A machine learning system will also test the significance of the data point and
20 determine what weight to assign to it in its model, but because it can consider all available data, it
21 has no need to begin by guessing the "meaning" of that data, before choosing to use it (as opposed
22 to other data), in its predictive model.¹⁰ Thus, a machine learning system does not need to attempt
23 to understand the semantic *meaning* of the data used in its modeling.¹¹

24 As a result, a data set containing a column labeled "sex" is no more useful to a machine
25 learning system than one labeled with an arbitrary set of numbers and letters. The system is equally
26

27 ¹⁰ Cynthia Rudin, *Stop explaining black box machine learning models for high stakes decisions and*
28 *use interpretable models instead*, Nature Machine Intelligence, 1(5), 206-215 (May 13, 2019).

¹¹ *Id.*

1 able to make use of a data set labeled “App Event 7F3AB9” as one with a clear natural language
2 title like “sex,” as the system can build a model placing weight on the data point for predictive
3 accuracy without “knowing” what this data means. This is true as to both the label for a given piece
4 of data and its content — the value “male” is no more useful than the value “1.” To be clear, this is
5 true due to the nature of machine learning systems’ operation; if, for example, “App Event
6 7F3AB9” actually corresponds to a person’s sex, that information — *i.e.*, the person’s sex — is
7 being communicated to and used by the machine learning system, but the machine learning system
8 need not understand this fact to build a model utilizing that data point.

9 There are many approaches to developing machine learning systems, but one of the most
10 common approaches for large systems are referred to as “neural networks.”¹² Neural networks pass
11 input data through layers in which calculations are performed that process the information.¹³ The
12 operation of a neural network is easiest to explain with a simple example, but it is necessary to first
13 provide some groundwork explanation.

14 Consider four numerical input data fields or features (*e.g.*, age, mass, height, number of
15 legs) and one field with a class (*e.g.*, dog, monkey, salmon, whale). One could take a simple
16 average of those four input fields to produce a single number. For example, age of 5 (yrs.), mass of
17 10,000 (lbs.), height of 13 (ft.), legs of 0, produces an average of 2,504. If one has many instances
18 of data of that type, some correlations could emerge, for example — all the large averages could
19 correspond to whales and all the small averages could correspond to dogs. If one knew the features
20 of a given instance, but not the class, one could make a rough prediction.

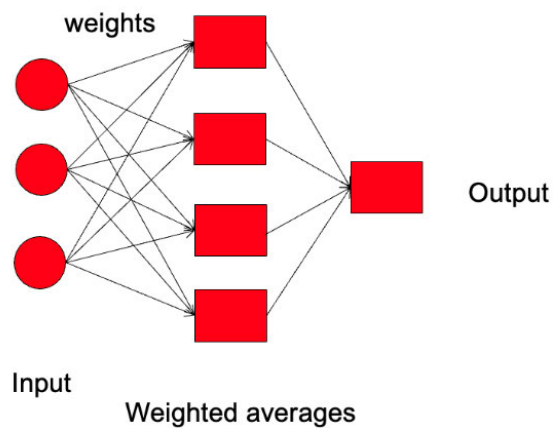
21 However, this approach just using a single simple average would likely struggle to produce
22 strong predictions distinguishing between the non-whale animals, in part because the whales’ mass
23 value will overwhelm differences between the other feature values. Therefore, a more accurate
24 approach might use multiple steps and weighted averages to produce more accurate predictions.
25 For example, perhaps one could start with a simple average and determine that if the result is
26 greater than 1,000, then the best prediction is that the animal is a whale, but if the average is less

27 _____
¹² Ethem Alpaydin, *Introduction to Machine Learning* (MIT Press, 2020).

28 ¹³ *Id.*

than 1,000 then a second step might be most predictively accurate if it placed almost the entirety of the weight (in a weighted average) on the number of legs, since among the non-whale animals, the number of legs is highly predictive of which animal the data is from.

A neural network is a machine learning system that can provide the sort of more sophisticated modeling illustrated in the prior paragraphs by using multiple layers and weighted averages across those layers.¹⁴ A neural network essentially takes input data and applies various weighted averages – or other similar transformations – to that data.¹⁵ Each weighted average is called a “node.” A diagram of a simple neural network with one layer of nodes is shown below:



The graphic above displays a single layer of weighted averages, whereas a functional neural network will have many layers. Each layer takes the results from the prior layer, and applies new weighted averages – or other similar transformations – to produce the node values for the next layer.¹⁶ The machine learning system is *trained* by iteratively adjusting the weighting — and other factors beyond the scope of this discussion¹⁷ — to produce a model that accurately makes a

¹⁴ *Id.*

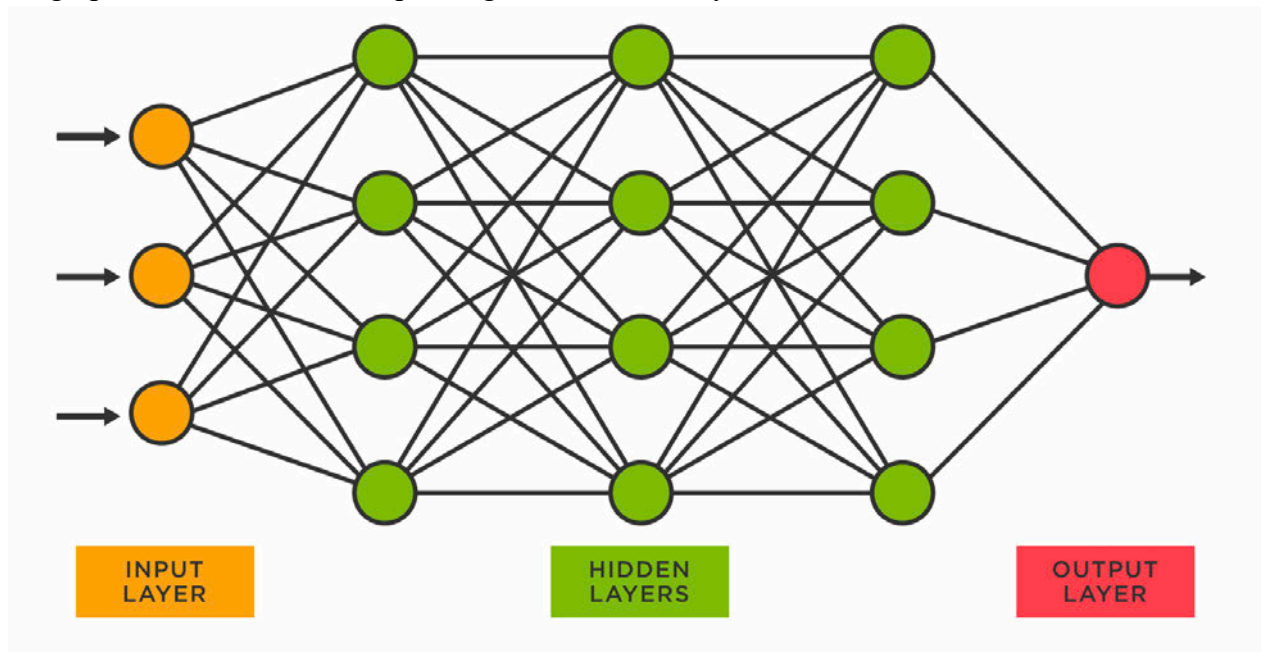
¹⁵ *Id.*

¹⁶ *Id.*

¹⁷ This description is intentionally simplified to accurately and clearly explain the basics of a neural network with sufficient detail to provide relevant background to the issues in my opinion, and does not account for significant variation in design, which would not change my opinions herein. For example, a model can have rules regarding when a node is “activated” for purposes of being used as an input in the next layer of transformations, but that concept merely adds to the complexity of the system and has no bearing on any of my opinions herein.

prediction.¹⁸ A sophisticated operational neural network can have many of these “hidden” layers.¹⁹

The graphic below shows a simple diagram of a multi-layered neural network.



The models used within neural networks are far more complex than a simple formula that weighs inputs at a simple singular rate. As a result, it not only would be excessively complex to explain the model’s decision making, but its decision is far abstracted from anything resembling a simple human intuition regarding the significance of various data points. Once the input data is passed from layer to layer in the synthesized form of various weighted averages (each weighting the data from the prior layer differently), the significance of any given piece of input data to the predictive accuracy of the model cannot be readily described. As a result, these neural network machine learning systems are often referred to as “black box” systems because it is not generally possible to look inside the system to see how exactly it functions, in any sort of intuitive way.²⁰

[continued]

¹⁸ *Id.*

¹⁹ *Id.*

²⁰ Cynthia Rudin, *Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead*, Nature Machine Intelligence, 1(5), 206-215 (May 13, 2019).

1 **IV. TOPIC 1:** [REDACTED]

2 **A. Background Concerning Meta and Its Advertising Business**

3 [REDACTED]
 4 [REDACTED]
 5 [REDACTED]
 6 [REDACTED]
 7 [REDACTED]
 8 [REDACTED]
 9 [REDACTED] The basic idea is that advertisers will pay more
 10 if their advertising efforts through Meta succeed at delivering the results sought by the advertiser.²⁶

11 [REDACTED]
 12 [REDACTED]
 13 [REDACTED]
 14 [REDACTED] Meta provides a similar example of how data can be used to target app users:
 15 “You can create ads targeting people based on the actions they are taking within your app. For

16
 17 ²¹ References herein to Facebook or Meta are interchangeable. The company Facebook was
 18 formally renamed Meta during 2021. The terms “app” and “application,” and “data” and
 19 “information” are also used interchangeably herein and are meant to be understood broadly to
 include data concerning or recording conversations, communications, interactions, among other
 things.

20 ²² See META-FRASCO-0000027524.

21 ²³ See *id.*

22 ²⁴ See META-FRASCO-0000027524.

23 ²⁵ See META-FRASCO-0000003207; META-FRASCO-0000003222; META-FRASCO-
 24 0000028221.

25 ²⁶ See generally, Facebook, Annual Report (Form 10-K) (Jan. 30, 2020) (“Marketers will not
 26 continue to do business with us, or they will reduce the budgets they are willing to commit to us, if
 27 we do not deliver ads in an effective manner, or if they do not believe that their investment in
 28 advertising with us will generate a competitive return relative to other alternatives. We have
 recently implemented, and we will continue to implement, changes to our user data practices. Some
 of these changes reduce our ability to effectively target ads, which has to some extent adversely
 affected, and will continue to adversely affect, our advertising business. If we are unable to provide
 marketers with a suitable return on investment, the pricing of our ads may not increase, or may
 decline, in which case our revenue and financial results may be harmed.”).

²⁷ See META-FRASCO-0000003207; META-FRASCO-0000003222; META-FRASCO-
 0000028221.

²⁸ See e.g., META-FRASCO-0000027524.

1 example, you can target people who previously used your app, but have not come back to your app
 2 within the last 90 days. Or you can target people who have added an item to their cart but didn't
 3 make a purchase."²⁹ Ads can also be targeted based on what websites people have interacted with,
 4 items they have purchased, or their similarity to other Meta users.³⁰

5 [REDACTED]
 6 [REDACTED]
 7 [REDACTED]
 8 [REDACTED]
 9 [REDACTED]
 10 [REDACTED]
 11 [REDACTED]
 12 [REDACTED]
 13 [REDACTED]
 14 [REDACTED]
 15 [REDACTED]
 16 [REDACTED].³⁴ Notably,
 17 even promotional material that is focused on targeting, nods to the additional work Meta does to
 18 drive engagement beyond targeting — for example, Meta states: "Facebook will automatically show
 19
 20
 21
 22

23 ²⁹ *Targeting by App Activity*, META FOR DEVELOPERS, <https://developers.facebook.com/docs/app-ads/targeting/by-app-activity/> (last visited May 7, 2023).

24 ³⁰ *Audience ad targeting*, FACEBOOK, www.facebook.com/business/ads/ad-targeting (available at <https://web.archive.org/web/20220308050101/https://www.facebook.com/business/ads/ad-targeting>) (last visited May 7, 2023).

25 ³¹ See META-FRASCO-0000003222; META-FRASCO-0000028221.

26 ³² See META-FRASCO-0000369441.

27 ³³ See META-FRASCO-0000008078; META-FRASCO-0000003207; META-FRASCO-0000003222; META-FRASCO-0000028212; META-FRASCO-0000028221; META-FRASCO-0000028246; META-FRASCO-0000028576; META-FRASCO-0000028584.

28 ³⁴ *Id.*

1 your ads to people most likely to find your ads relevant,” before adding “you can further target your
2 ad delivery with three audience selection tools.”³⁵

3 [REDACTED]
4 [REDACTED]
5 [REDACTED]
6 [REDACTED]
7 [REDACTED]
8 [REDACTED]
9 [REDACTED]
10 [REDACTED]
11 [REDACTED]
12 [REDACTED]
13 [REDACTED]
14 [REDACTED]
15 [REDACTED]
16 [REDACTED]
17 [REDACTED]
18 [REDACTED]
19 [REDACTED]

23 ³⁵ *Audience ad targeting*, FACEBOOK, www.facebook.com/business/ads/ad-targeting (available at
24 [https://web.archive.org/web/20220308050101/https://www.facebook.com/business/ads/ad-](https://web.archive.org/web/20220308050101/https://www.facebook.com/business/ads/ad-targeting)
targeting) (last visited May 7, 2023).

25 ³⁶ See Wooldridge Dep. Tr. at 81:3-12.

26 ³⁷ META-FRASCO-0000019555.

27 ³⁸ See Wooldridge Dep. Tr. at 164:2-8.

28 ³⁹ META-FRASCO-0000019555.

⁴⁰ *Id.*

⁴¹ See *id.*

1 [REDACTED]

2 [REDACTED]

3 [REDACTED]

4 [REDACTED]

5 [REDACTED]

6 [REDACTED]

7 [REDACTED] ⁴³

8 [REDACTED]

9 [REDACTED] For example, Meta states that “[o]ver time, as more people view an ad, share

10 feedback on it or click through to make a purchase on an advertiser’s website, [Meta’s] models get

11 better at predicting the estimated action rate and ad quality.”⁴⁴ To this end, Meta’s promotional

12 material informs advertisers that, because “billions of people use our apps and engage with ads each

13 day, our system gets lots of information to help improve its calculations, furthering our ultimate

14 goal of maximizing value for you and your community alike.”⁴⁵ [REDACTED]

15 [REDACTED]

16 [REDACTED]

17 [REDACTED]

18 [REDACTED]

19 [REDACTED]

20 [REDACTED]

21 [REDACTED]

22 [REDACTED]

23

24 ⁴² Statements herein should be understood as inclusive and not exhaustive. For example, [REDACTED]

25 [REDACTED]

26 ⁴³ META-FRASCO-0000369580.

27 ⁴⁴ *Driving Optimization With Machine Learning*, META,

28 <https://www.facebook.com/gpa/blog/driving-optimization-with-machine-learning> (last visited May 7, 2023).

⁴⁵ *Id.*

1 B. [REDACTED]
2 [REDACTED]
3 [REDACTED]
4 [REDACTED]
5 [REDACTED]
6 [REDACTED]
7 [REDACTED]
8 [REDACTED]
9 [REDACTED]
10 [REDACTED]
11 [REDACTED]
12 [REDACTED]
13 [REDACTED]
14 [REDACTED]
15 [REDACTED]
16 [REDACTED]
17 [REDACTED]
18 [REDACTED]
19 [REDACTED]
20 [REDACTED]
21 [REDACTED]

22 ⁴⁶ I understand a separate expert is providing a report that focuses on the function of the Facebook
23 SDK, and my explanation here is intentionally limited to providing the necessary background to
explain the matters I have been asked to opine on.

24 ⁴⁷ See FLO-00094771.

25 ⁴⁸ [REDACTED]
26 [REDACTED]
27 [REDACTED]
28 [REDACTED]

Meta's response to Interrogatory No. 1, served on January 30, 2023 and verified by Tobias Wooldridge.

1 [REDACTED]
 2 [REDACTED]
 3 [REDACTED]
 4 [REDACTED]
 5 [REDACTED]
 6 [REDACTED]
 7 [REDACTED]
 8 [REDACTED]
 9 [REDACTED]

10	[REDACTED]	[REDACTED]
11	[REDACTED]	[REDACTED]
12	[REDACTED]	[REDACTED]
13	[REDACTED]	[REDACTED]
14	[REDACTED]	[REDACTED]

15 [REDACTED]
 16 [REDACTED]
 17 [REDACTED]
 18 [REDACTED]

19 [REDACTED]
 20 [REDACTED]
 21 [REDACTED]
 22 [REDACTED]
 23 [REDACTED]

⁵⁰ *Id.*; META-FRASCO-0000001167.

⁵¹ META-FRASCO-0000001167.

⁵² See FLO-00001891-99.

⁵³ For the avoidance of doubt, [REDACTED]

HealthKit is a central repository for health and fitness data on iPhone and Apple Watch.

⁵⁵ Meta's response to Interrogatory No. 1, served on January 30, 2023 and verified by Tobias Wooldridge.

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[graphic on following page]

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28 ⁵⁶ Meta's response to Interrogatory No. 1, served on January 30, 2023 and verified by Tobias Wooldridge (footnote omitted).

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[REDACTED]

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[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

[REDACTED]

⁵⁷ Wooldridge Dep. Tr. at 154:10-19.

⁵⁸ *See generally* Wooldridge Dep. Tr. at 154:10-55:2.

⁵⁹ *See generally* Wooldridge Dep. Tr. at 155:3-56:3.

⁶⁰ Wooldridge Dep. Tr. at 156:7-10.

1 [REDACTED]
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4 [REDACTED]
5 [REDACTED]
6 [REDACTED]
7 [REDACTED]
8 [REDACTED]
9 [REDACTED]
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11 [REDACTED]
12 [REDACTED]
13 [REDACTED]
14 [REDACTED]
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16 [REDACTED]
17 [REDACTED]
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19 [REDACTED]
20 [REDACTED]
21 [REDACTED]
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24 [REDACTED]
25 [REDACTED]

⁶¹ See generally Wooldridge Dep. Tr. at 158:18-22.

⁶² Wooldridge Dep. Tr. at 160:15-161:7

⁶³ Wooldridge Dep. Tr. at 161:4-7.

1 [REDACTED]
2 [REDACTED]
3 [REDACTED]
4 [REDACTED] See
5 e.g., META-FRASCO-0000369598 [REDACTED]
6 [REDACTED]
7 [REDACTED]; META-FRASCO-0000024407 [REDACTED]
8 [REDACTED]
9 META-FRASCO-0000006275 [REDACTED]
10 [REDACTED]

11 Sometimes machine learning algorithms use engineered or composed features. These are
12 features created by taking existing features (*i.e.*, data points) and combining them in some way to
13 produce new features.⁶⁵ For example, a simple engineered feature could indicate if a user had
14 interacted with any one of a set of features in an app. Whether they interacted one time with one
15 feature or many times with many features, this composite feature could have a value of "1" for any
16 interaction and a "0" for no interaction. Those working in machine learning would still refer to the
17 system as “using” the original data that was ingested, even if it has been transformed into new
18 features. If the composed features (*i.e.*, transformed data) is used by the machine learning system,
19 then the original ingested data used to create those composed features is itself still being used.

20 [REDACTED]

21 [REDACTED]⁶⁶ [REDACTED]

22 [REDACTED]

23 [REDACTED]

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26 ⁶⁴ I discuss these “user controls and other things” in the following subsection.

27 ⁶⁵ Dong, G., & Liu, H. (Eds.). (2018). *Feature engineering for machine learning and data analytics*. CRC Press.

28 ⁶⁶ See Meta’s response to Interrogatory No. 1, served on January 30, 2023 and verified by Tobias Wooldridge (footnote omitted).

1 3. [REDACTED]

2 [REDACTED]

3 [REDACTED]

4 [REDACTED]

5 [REDACTED]

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7 [REDACTED]

8 [REDACTED]

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10 [REDACTED]

11 [REDACTED]

12 [REDACTED]

13 [REDACTED]

14 [REDACTED]

15 [REDACTED]

16 [REDACTED]

17 [REDACTED]

18 [REDACTED]

19 [REDACTED]

20 [REDACTED]

21 [REDACTED]

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⁶⁷ Meta's Response to Interrogatory No. 1, served on January 30, 2023 and verified by Tobias Wooldridge.

⁶⁸ *Id.*

⁶⁹ *Id.*

⁷⁰ Wellman Dep. Tr. at 287:19–288:11; Kiss Dep. Tr. at 285:9–286:20.

⁷¹ *See generally* [REDACTED]

1 [REDACTED]⁷² [REDACTED]
2 [REDACTED]
3 [REDACTED]
4 [REDACTED]
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6 [REDACTED]
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8 [REDACTED]
9 [REDACTED]
10 [REDACTED]
11 [REDACTED]
12 [REDACTED]
13 4. [REDACTED]
14
15 In training, machine learning models make use of all data made available to that system.
16 While humans may be involved in configuring various aspects of a machine learning system, such
17 as deciding on the number of layers to use in a neural network, the actual training process runs in an
18 automated fashion — this automation is a core aspect of what makes machine learning what it is.
19 As a result, the system necessarily uses all data that has been made available to the system, or put
20 differently, to say the data is made available to the system for training purposes is to say the data is
21 used in that training process. The outcome of the training process is a model that weighs different
22 data differently, but within the training process, all data is equal in that it is all just an input that is
23 used in the training process. [REDACTED]
24 [REDACTED]
25

26 ⁷² Meta's Suppl. Resps. & Objs. to Pls.' First Set of Interrogs. Response to Interrogatory 3, served
on October 31, 2022.

27 ⁷³ *Id.*

28 ⁷⁴ Meta's Suppl. Resps. & Objs. to Pls.' First Set of Interrogs. Response to Interrogatory 3, served
on October 31, 2022.

1 [REDACTED]
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12 [REDACTED]
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14 [REDACTED]
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16 [REDACTED]
17 [REDACTED]
18 [REDACTED]
19 [REDACTED]
20 [REDACTED]
21 [REDACTED]
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23 [REDACTED]
24 [REDACTED]

⁷⁵ See META-FRASCO-0000020292; META-FRASCO-0000020303.

⁷⁶ See META-FRASCO-0000008078 [REDACTED]

[REDACTED] META-FRASCO-0000369438; META-FRASCO-0000369515 [REDACTED]

⁷⁷ See *id.*

This can be simply illustrated with an example. Consider the Custom App Event Data point with the title “EVENT_5,” [REDACTED]

[REDACTED]

[REDACTED] But the semantic meaning of this datapoint is not relevant to whether that data can be used – and especially not relevant to its use by a machine learning system that can consider billions of data points in search of relationships – to draw conclusions. Consider a data set that includes the following:

Facebook User ID	Clicked on Advertisement for Online Counseling	EVENT 5
Example ID1	Yes	1
Example ID2	Yes	1
Example ID3	Yes	0
Example ID4	Yes	1
Example ID5	Yes	1
Example ID6	No	0
Example ID7	No	0
Example ID8	No	1
Example ID9	No	0
Example ID10	No	0

From data like this, an inference could be drawn that the data value “1” in Event_5 is predictive of whether a person will click advertisements for online counseling. This inference can be drawn without any understanding of what Event_5 means. Then a machine learning system may predict that users with the data point Event_5 and the value “1” are more likely to click advertisements for a future advertisement for online counseling. This is of course, a highly simplified example, in reality a model created through a machine learning system will rely on far more data to make predictions, but the point is that this example illustrates how the predictive value of data is not dependent on an understanding of that data’s meaning.

Machine learning algorithms often train on thousands of instances. Part of the machine learning process is to give more weight to features that are more useful. While it may seem like there are logical reasons some features may be more useful (*e.g.*, it might be very useful to an

1 algorithm that is predicting if someone is pregnant to know that they bought a pregnancy test), that
2 is often not the case.⁷⁸ The patterns that machine learning algorithms detect may not make any
3 sense to humans.

4 For example, someone's social circle influences what they see on social media, and that will
5 in turn impact what they interact with. The fact that User A has interacted with the same things as
6 other users may allow an algorithm to infer that User A shares things in common with those other
7 users.⁷⁹ The content or meaning of the shared items is almost meaningless, but it tells an algorithm
8 about a person because it shows who the person interacts with.

9 In other situations, it could be that most people who buy a pregnancy test are pregnant. But,
10 if only a small percentage of pregnant people bought pregnancy tests, data about pregnancy tests
11 may not be nearly as predictively useful to a machine learning system as data about some other
12 feature; a more common action may be more useful to a predictive model.

13 As described above, it is not clear which data will be useful for training a model. For
14 example, one study looked at using people's "likes" on Facebook to predict a range of personal
15 attributes, including IQ score. Among the strongest predictors of high IQ was if someone liked the
16 page for Curly Fries.⁸⁰ Note that this project used a simpler linear/logistic regression algorithm,
17 rather than a neural network, which allowed for some insight into the predictive power of specific
18 features. Artificial intelligence does not tell us *why* this is a strong connection, and there is no
19 logical reason the two would be connected. Nonetheless, it is a strong predictor. This is just one
20 example of how connections that seem illogical to humans are actually quite useful in making
21 predictions. One conclusion from this, is that the Flo Custom App Event Data may have been
22 useful in determining who to serve ads on topics related to reproductive health, but may also have
23

24 ⁷⁸ ⁷⁸Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable
25 from digital records of human behavior. *Proceedings of the national academy of sciences*, 110(15),
5802-5805.

26 ⁷⁹ Bisgin, H., Agarwal, N., & Xu, X. (2012). A study of homophily on social media. In *Social
27 Network Mining, Analysis, and Research Trends: Techniques and Applications* (pp. 17-34). IGI
Global.

28 ⁸⁰ Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from
digital records of human behavior. *Proceedings of the national academy of sciences*, 110(15), 5802-
5805.

1 been useful in determining who to serve ads on any topic, even where the relationship between the
2 data and the advertisement is wholly unintuitive.

3 Combinations of features can also be useful. For example, the fact that I use a certain puzzle
4 game app may not help an algorithm predict much on its own. Similarly, the fact that I am a student
5 at a certain university may not mean much on its own. But the combination could be very
6 meaningful. If a certain game is unpopular at the university overall but very popular among
7 members of a specific sports team, an algorithm may be able to very accurately predict that a
8 student plays rugby if she attends the University of Michigan and plays Two Dots, even though the
9 two important features seem to have nothing to do with rugby.

10 Because the patterns an algorithm looks for are statistical and not necessarily meaningful or
11 logical to humans, there is no way to know a priori which data will be useful for predicting any
12 given attribute. Thus, the widespread consensus view among machine learning scholars is that the
13 overarching rule is that it is better to have as much data as possible.

14 When an algorithm is building a model, it is almost always the case that more data makes
15 the model more accurate.⁸¹ Especially with more complex algorithms – [REDACTED]
16 – it is important to use more data. “The complexity of the learning algorithm is critical and should
17 be calibrated with the complexity of the data. The more sophisticated the underlying algorithm, the
18 more data are needed.”⁸² It is possible that a certain point there are diminishing returns to having
19 additional data, but that would only reduce its usefulness and not reduce its usefulness to a nullity.

20 [REDACTED]

21 [REDACTED]

22 [REDACTED]

23 [REDACTED]

24 [REDACTED]

25 [REDACTED]

26 ⁸¹ Martens, D., & Provost, F. (2011). Pseudo-social network targeting from consumer transaction
27 data.

28 ⁸² Bzdok, D., Krzywinski, M., & Altman, N. (2017). Points of Significance: Machine learning: a
primer. Nature methods, 14(12), 1119.

1 machine learning systems – especially neural network systems – it is not feasible to state or even
2 cognizable to ask whether a given advertisement was delivered *because* of the Flo App User Data
3 (as opposed to other data) or even to quantify the effect the Flo App User Data had on the delivery
4 of a given advertisement. This is not because the effect of the data was not significant, but because
5 the black box nature of machine learning systems makes these sorts of simplistic cause-effect
6 conclusions infeasible. [REDACTED]

7 [REDACTED]
8 [REDACTED]
9 [REDACTED]
10 [REDACTED]
11 [REDACTED]
12 [REDACTED]
13 [REDACTED]
14 [REDACTED]
15 [REDACTED]

16 While I have addressed above the consensus view that generally more data makes a machine
17 learning based system more effective, there are situations in which having more data can impose
18 costs that outweigh the benefits. For example, the most obvious downside to making more data
19 available to a machine learning system is cost – retaining large amounts of data is expensive and
20 training a model on more data takes longer.

21 **D.** [REDACTED]
22 [REDACTED]
23 [REDACTED]
24 [REDACTED]
25 [REDACTED]
26 [REDACTED]
27 [REDACTED]
28 [REDACTED]

Many of Meta's products, such as search, ads ranking and Marketplace, utilize AI models to continuously improve user experiences. As the performance of hardware we use to support training infrastructure increases, we need to scale our data ingestion infrastructure accordingly to handle workloads more efficiently. GPUs, which are used for training infrastructure, tend to double in performance every two years, while the performance of CPUs, used for data reading computation, increases at a much slower pace in the same time frame. To facilitate the level of data ingestion required to support the training models supporting our products, we've had to build a new data ingestion infrastructure as well as new last-mile transformation pipelines. By optimizing areas of our data ingestion infrastructure, we improved our power budget requirement by 35-45%, allowing us to support a growing number of AI models in our power constrained data centers.⁸⁶

⁸³ Wooldridge Dep. Tr. at 50:14-24.

⁸⁴ See Wooldridge Dep. Tr. at 74:2-8.

⁸⁵ See META-FRASCO-0000020292, at META-FRASCO-0000020307.

⁸⁶ Aarti Basant, *Scaling data ingestion for machine learning training at Meta*, ENGINEERING AT META (Sept. 19, 2022), <https://engineering.fb.com/2022/09/19/ml-applications/data-ingestion-machine-learning-training-meta>.

⁸⁷ See META-FRASCO-0000022459.

⁸⁸ META-FRASCO-0000022438, at META-FRASCO-0000022467.

⁸⁹ META-FRASCO-0000022459.

V. TOPIC 2: GOOGLE USED THE FLO CUSTOM APP EVENT DATA

The Flo Custom App Event Data was used by Google; it was made available to Google's machine learning systems used for Google's advertising business.

A. Background on Google and Its Advertising Business

Google derives a significant portion of its revenue through its advertising business. One of Google's primary advertising products is known as "Google Ads." Google Ads helps advertisers, such as apps, to create ads and launch ad campaigns.⁹¹ Google's advertising business uses machine learning systems in a variety of ways to improve the value proposition of that business. For instance, Google Ad's Universal App Campaigns ("UAC") are used by app developers to advertise their apps across multiple platforms to drive app installs and conversions.⁹² UAC's targeting and bidding features are driven by its proprietary, 100% machine learning based technology, using more than 100 data signals that "result in hundreds of millions [of] signal combinations."⁹³ For its machine learning technology to work, Google's UACs require data to "feed[] the machine."⁹⁴

Another way machine learning is used is to make predictions for its Google Analytics for Firebase users.⁹⁵ The Google Analytics infrastructure collects and processes events from millions of apps and is "tightly integrate[d]" with UAC's machine learning technology.⁹⁶ Google's Firebase mobile app development platform was built on top of this infrastructure to allow app developers to

⁹⁰ META-FRASCO-0000022459.

⁹¹ GOOG-FLO-00000132; GOOG-FLO-00000001.

⁹² GOOG-FLO-00064255; GOOG-FLO-00078304.

⁹³ GOOG-FLO-00064255.

⁹⁴ *Id.*

⁹⁵ GOOG-FLO-00020199.

⁹⁶ GOOG-FLO-00091826; GOOG-FLO-00062455.

1 “leverage” the personal user data collected by Google Analytics.⁹⁷ App developers use Google
 2 Analytics for Firebase to understand how app users engage with their app.⁹⁸ Google Analytics for
 3 Firebase also provides app developers with a set of features called Analytics Intelligence which uses
 4 machine learning to provide insight into changes or trends within that app’s data.⁹⁹

5 Google supports the machine learning systems utilized in its advertising business with a
 6 stream of data from various sources. One source for this data is Google’s SDKs, such as the Google
 7 Analytics for Firebase (“GA4F”) SDK, which Google makes publicly available to app developers
 8 for free. Google entices app developers to use these SDKs by providing various analytics to those
 9 app developers. For example, Google processes data transmitted to it by its Google GA4F SDK
 10 (described below) and generates reports, which are made available to app developers in a dashboard
 11 accessible through an information console.¹⁰⁰ The dashboard provides app developers with
 12 summary and detailed data about app users.¹⁰¹

13 Despite offering the GA4F SDK for “free,” Google views it as “driving value” and adding
 14 revenue to the company, particularly Google’s Ads business.¹⁰² Google considers the data from apps
 15 using the SDK to be a source of value as the data can be used to enhance Google’s other products
 16 and features.¹⁰³ Google intended to create a “virtuous cycle” of value by offering GA4F for free:
 17 developers would receive value from GA4F for measuring structured event data and that data would
 18 then become usable across Google’s products and services.¹⁰⁴

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23 ⁹⁷ GOOG-FLO-00091826.

24 ⁹⁸ Ganem 30(b)(6) Dep. Tr. at 39:3-13. The Google Analytics for Firebase was a former brand that
 is now part of Google Analytics. *Id.* at 16:14-16.

25 ⁹⁹ GOOG-FLO-00020391.

26 ¹⁰⁰ GOOG-FLO-00037744; GOOG-FLO-00077487.

27 ¹⁰¹ GOOG-FLO-00037744.

28 ¹⁰² GOOG-FLO-00091826.

¹⁰³ GOOG-FLO-00088918.

¹⁰⁴ GOOG-FLO-00088918; GOOG-FLO-00088930.

B. Google Used the Custom App Event Data in Content Delivery Optimization

1. Google Received the Flo Custom App Event Data and Made This Data Available to Its Machine Learning Systems

Google operated multiple SDKs, but in this report I have focused on the GA4F SDK.¹⁰⁵ The GA4F SDK is an app measurement tool provided by Google to app developers free of charge.¹⁰⁶ The GA4F SDK can provide app developers with insights on app usage and user engagement.¹⁰⁷ To use the GA4F SDK, the app developer first adds the GA4F SDK to its app.¹⁰⁸ The GA4F SDK collects information concerning both “events” occurring within applications and “user properties” defined by the application developer.¹⁰⁹ The GA4F SDK can collect information based on events defined by Google, and the corresponding data Google receives from these events would fit into the definition herein of “Standard App Event Data.” App developers can also define custom app events, which can send data chosen by the app developer corresponding to an application user’s interactions within the application, based on events chosen by the app developer. The corresponding data received by Google from these events would fit into the definition herein of “Custom App Event Data.”¹¹⁰

Flo integrated the GA4F SDK into the Flo Health App.¹¹¹ Flo created and used Custom App Events that resulted in data concerning Flo App users being received by Google through the GA4F SDK. In this litigation, Google produced a spreadsheet showing Flo Custom App Event Data that it received through the GA4F, from June 2016 until June 2021, which included hundreds of different Custom App Event titles and millions of occurrences of Google receiving this Flo Custom App

¹⁰⁵ I have only focused on the GA4F SDK because my analysis, even so limited, has provided me a sufficient basis to conclude that Google used the relevant data. Whether or not Google also used data collected through its other SDK – Fabric Answers SDK – would not change my conclusion.

¹⁰⁶ GOOG-FLO-00037744.

¹⁰⁷ GOOG-FLO-00037744.

¹⁰⁸ GOOG-FLO-00073263.

¹⁰⁹ GOOG-FLO-00037788.

¹¹⁰ GOOG-FLO-00073218; GOOG-FLO-00073263; GOOG-FLO-00077973; GOOG-FLO-00077963; GOOG-FLO-00037744; GOOG-FLO-00075072; *See* Exhibit C to Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One.

¹¹¹ *See* Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One, Responses to Interrogatory Nos. 1 and 2; Ganem 30(b)(6) Dep. Tr. at 34:11-13.

1 Event Data.¹¹² [REDACTED]

2 [REDACTED]¹¹³ The table below shows several examples of the Custom App
3 Event Data points that Google received through the Flo App event and the corresponding
4 description of that event.¹¹⁴

<i>Event Title</i>	<i>Event Description</i> ¹¹⁵
R_SELECT_LAST_PERIOD_DATE	[REDACTED]
R_SELECT_PERIOD_LENGTH	[REDACTED]
R_PREGNANCY_WEEK_CHOSEN_UNKNOWN	[REDACTED]
R_PREGNANCY_METHOD_DATE	[REDACTED]
EVENT 2	[REDACTED]

10 The data received by Google through the GA4F SDK was used for a variety of purposes,
11 including providing analytics to the app developer that had integrated the GA4F SDK into their
12 application.¹¹⁶ But use of the data is not limited to the app developer. Google also uses the data
13 collected from the GA4F SDK to help train its models to be faster and more accurate, and to
14 improve its machine learning-based products and campaigns (“feeding the machine”).¹¹⁷ Indeed,
15 because Google’s machine learning-based products are reliant on data for model improvements and
16 performance features, Google encourages app developers to use Google Analytics for Firebase for
17 data collection.¹¹⁸ As an example of Google’s desire to collect this data, when Flo eventually
18 expressed concerns about using Google’s SDKs, Google tried repeatedly to convince Flo Health to
19 use the GA4F SDK anyway.¹¹⁹

20 Data received through the GA4F SDK could also be made available to the separate Google
21 product called “Google Ads.” As discussed below, one way the data received through the GA4F
22

23 ¹¹² See Exhibit C to Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One.

24 ¹¹³ See FLO-00001891.

25 ¹¹⁴ For the avoidance of doubt, Google did not necessarily have access to these descriptions, and my
26 opinions herein are not dependent on any assumption that Google had access to such descriptions.

27 ¹¹⁵ See FLO-00001891.

28 ¹¹⁶ GOOG-FLO-00037744.

¹¹⁷ GOOG-FLO-00064255.

¹¹⁸ GOOG-FLO-00064255.

¹¹⁹ GOOG-FLO-00057427.

1 SDK would be made available to the Google Ads product was if that product was “linked” with a
 2 Google Ads account. Documents show that Flo did link its Google Ads account to its GA4F SDK
 3 account which indicates data received through the GA4F SDK was shared with Google Ads.¹²⁰

4 The GA4F SDK was designed to seamlessly integrate customer’s Google Analytics accounts
 5 with other Google products. Google achieved this integration through a process called “linking,”
 6 whereby a customer links their Google Analytics for Firebase account to their other Google product
 7 accounts.¹²¹ Google also encouraged linking GA4F SDK accounts with Google Ads accounts by
 8 designing their system such that GA4F SDK would specifically track the developers Google Ads
 9 campaigns (e.g., whether that campaign was succeeding at generating the desired result),¹²² through
 10 a feature known as Project Uno.¹²³

11 Flo Health had at least two Google Ads accounts: Account 355-062-3707¹²⁴ and 807-232-

12 5127.¹²⁵ Flo linked its GA4F SDK account with its Google Ads accounts,¹²⁶ meaning (as explained
 13 in the prior paragraph), the Flo Custom App Event Data Google received through the GA4F SDK
 14 was made available to Google’s systems for Google’s own purposes.

15 If an app linked its Google Ads and Google Analytics for Firebase accounts, Google became
 16 a “co-controller” of that app’s data, allowing Google to more generally use the app’s data to
 17 enhance Google’s products and features.¹²⁷ Once the data is available to Google Ads to train
 18 machine learning models, it can be used in several ways. For example, Google Ads uses machine
 19 learning in Google App Campaigns (formerly known as Universal App Campaigns) used by app
 20

21
 22 ¹²⁰ See Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One, Response to Interrogatory No. 1.

23 ¹²¹ GOOG-FLO-00077979; GOOG-FLO-00088918; GOOG-FLO-00093185; GOOG-FLO-00091874.

24 ¹²² Ganem 30(b)(1) Dep. Tr. at 38:1-20.

25 ¹²³ Ganem 30(b)(1) Dep. Tr. at 38:1-20.

26 ¹²⁴ See Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One, Response to Interrogatory No. 1.

27 ¹²⁵ GOOG-FLO-00084738; *see also* Volchenok Dep. Tr. at 77:4-79:7.

28 ¹²⁶ See Google’s Fourth Supplemental Responses to Plaintiffs’ Interrogatories, Set One, Responses to Interrogatory Nos. 1 and 2; Ganem 30(b)(6) Dep. Tr. at 34:11-13.

¹²⁷ GOOG-FLO-00088918; GOOG-FLO-00077979; GOOG-FLO-00093185.

1 developers to advertise their apps to new users.¹²⁸ Universal App Campaigns for Engagement
 2 (UACe), which enables app developers to re-engage existing app users who already have the app,
 3 also uses machine learning.¹²⁹ The targeting and bidding features within Google Ads' Universal
 4 App Campaigns are driven 100% by Google's proprietary machine learning technology, which is
 5 based on more than 100 data signals.¹³⁰

6 **2. Google's Use of the Flo Custom App Event Data Was Not Restricted**

7 Except as discussed below, I am not aware of any process within Google's systems that
 8 would have limited Google's use of the Flo Custom App Event data. If such a system were brought
 9 to my attention, I would evaluate its relevance to my conclusions herein, and at this time my
 10 conclusion assumes no such system exists.

11 I am aware that Google had certain controls in place to limit the use of sensitive data, but my
 12 understanding is that notwithstanding these controls, Flo's data was ingested and used by Google's
 13 systems.

14 First, Google's use of data could be restricted based on an application being labeled as
 15 "sensitive" by Google's systems. The Flo Health App was given this "sensitive" label.¹³¹
 16 However, my understanding is that this only restricted the use of the data for certain tools offered
 17 by Google Ads, but not all tools offered by Google Ads. For example, Google also does not
 18 prohibit "sensitive" apps from using Google's predefined audience feature to target advertisements
 19 based on users' affinity, demographics, detailed demographics, and life events.¹³² As another
 20 example, while Google Ad campaigns were prohibited from using the user data from an app marked
 21 sensitive after 2020,¹³³ prior to this date, apps categorized as sensitive *could* use Universal App
 22 Campaigns for Engagement to further target advertisements to users who had already downloaded
 23

24 _____
 25 ¹²⁸ GOOG-FLO-00064255; GOOG-FLO-00078297; Ewing Dep. Tr. at 50:5-12; Volchenok Dep.
 Tr. 28:19-29:8.

26 ¹²⁹ Ewing Dep. Tr. at 128:23-129:7.

27 ¹³⁰ GOOG-FLO-00064255; GOOG-FLO-00078304.

28 ¹³¹ Lam 30(b)(6) Dep. Tr. at 94:11-95:11; 96:22-97:11.

¹³² GOOG-FLO-00000122; GOOG-FLO-00000122; Ewing Dep. Tr. 82:5-83:5.

¹³³ GOOG-FLO-00084753.

1 the app.¹³⁴ While the “sensitive” label may have restricted Google’s ability to receive¹³⁵ and use
 2 the data for certain purposes, it would not have limited Google’s ability to use the data in its
 3 machine learning systems for other purposes.

4 Second, Google developed a system known as “non-personalized advertising signals”
 5 (“NPA”), wherein data could be flagged as “NPA” and its use could then be restricted such that it
 6 would not be used for “personalized advertising purposes.”¹³⁶ This system required the App
 7 Developer to self-select into this restriction and was not turned on by default by Google.¹³⁷

8 I have not seen any documents or testimony that would lead me to believe Flo self-selected
 9 into this category, and therefore have assumed the default status (of not using the NPA flag) was
 10 employed. However, regardless of whether the NPA flag was employed by Flo, this flag merely
 11 restricted “personalized” advertising, and would not limit Google’s ability to use the data for other
 12 purposes, including within its machine learning systems.

13 Furthermore, while it appears that at certain points in time Flo’s ability to engage in certain
 14 activities on Google’s systems were restricted, these restrictions were not always in place, such that
 15 – regardless of whether or not the NPA flag was set for some Flo App Event Data – this alone would
 16 not indicate to me that any potential restrictions that theoretically follow from the NPA tag were
 17 effectuated. For example, one restriction on NPA flagged data was supposedly that it could not be
 18 used for remarketing,¹³⁸ which refers to using lists of existing users of an app to whom the app
 19 wants to reengage with,¹³⁹ and Flo’s remarketing lists were disabled for personalized advertising at
 20 least once on September 28, 2019,¹⁴⁰ suggesting that Flo was able to use remarketing at least for
 21 some periods before this time, indicating that Flo App Event data was either not flagged as NPA

22
 23
 24 ¹³⁴ Ewing Dep. Tr. at 128:23-129:7; GOOG-FLO-00090263 at ‘265.

25 ¹³⁵ GOOG-FLO-00088952.

26 ¹³⁶ GOOG-FLO-00088952.

27 ¹³⁷ GOOG-FLO-00088952; Ganem 30(b)(1) Dep. Tr. at 44:6-17.

28 ¹³⁸ Ganem 30(b)(6) Dep. Tr. at 111:9-112:15.

¹³⁹ Ganem 30(b)(6) Dep. Tr. at 109:25-110:4.

¹⁴⁰ GOOG-FLO-00082938.

1 before then, or if it was, the flag did not restrict the use of the Flo App Event Data even for
2 remarketing purposes.¹⁴¹

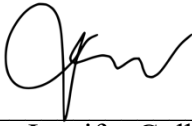
3 **C. By Making the Custom App Event Data Available to Google's Machine**
4 **Learning Systems, Google Used the Data to Improve Its Advertising Business**

5 As stated in the prior subsection, Google used machine learning systems to improve a
6 variety of functions within its Google Analytics for Firebase product and within its Google Ads
7 product. By making Flo Custom App Event Data available in training and operating those machine
8 learning systems, Google used that Flo Custom App Event Data. My general analysis of the use of
9 data within such machine learning systems is described in Section IV(B), and the following points
10 addressed more fully therein apply here as well: (1) through making the data available to Google's
11 machine learning systems, the data would be used by Google regardless of whether Google's
12 systems understood its semantic meaning; (2) access to such data would be expected to improve the
13 performance of those systems; and (3) it is not feasible to narrowly assess the cause-effect
14 relationship of data and particular advertising decisions, within a sophisticated machine learning
15 system, but it is plausible that making Flo Custom App Event Data available to Google's systems
16 could have influenced decisions regarding who to show particular advertisements, including both
17 adds with a clear connection to women's health and pregnancy but also including ads on any topic.

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26 ¹⁴¹ Similarly, while Flo Health also had thousands of ads disapproved by Google Ads for containing
27 sensitive information related to pregnancy and birth control (*see* GOOG-FLO-00081653; GOOG-
28 FLO-00084738; GOOG-FLO-00084753; GOOG-FLO-00082935), many of these ads were
eventually approved after being manually reviewed by Google Ads, meaning they were able to be
served (GOOG-FLO-00082943; GOOG-FLO-00082931; GOOG-FLO-00081701; Volchenok Dep.
Tr. at 74:3-7).

1 I declare under penalty of perjury under the laws of the State of California and the United
2 States that the foregoing is true and correct.

3
4 Executed on this 9 day of May, 2023 in Silver Spring, MD.

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7 Jennifer Golbeck, Ph.D.
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Appendix A

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- [GKH⁺22] Dritjon Gruda, Dimitra Karanatsiou, Paul Hanges, **Jennifer Golbeck**, and Athena Vakali. Dont go chasing narcissists: A relational-based and multiverse perspective on leader narcissism and follower engagement using a machine learning approach. *Personality and Social Psychology Bulletin*, page 01461672221094976, 2022.
- [GKM⁺21] Dritjon Gruda, Dimitra Karanatsiou, Kanishka Mendhekar, **Jennifer Golbeck**, and Athena Vakali. I alone can fix it: Examining interactions between narcissistic leaders and anxious followers on twitter using a machine learning approach. *Journal of the Association for Information Science and Technology*, 72(11):1323–1336, 2021.
- [Gol23] **Jennifer Golbeck**. Photo aesthetics as a factor in trust and interest assessments. *First Monday*, May, 2023.

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Notarization. I have read the following and certify that it is a current and accurate statement of my professional record, as of April 30, 2023.

Signature:

A handwritten signature in black ink, appearing to read 'Jennifer Golbeck', with a stylized flourish at the end.

1 Personal Information

1.A University Appointments

8/2018–present	Professor, College of Information Studies Affiliate Professor, Computer Science Department Affiliate Professor, Merrill School of Journalism University of Maryland (College Park, Maryland)
8/2013–8/2018	Associate Professor, College of Information Studies University of Maryland (College Park, Maryland)
8/2007–8/2013	Assistant Professor, College of Information Studies University of Maryland (College Park, Maryland)

1.B Education

8/2001–5/2005	University of Maryland (College Park, Maryland) Doctor of Philosophy in Computer Science
9/1999–6/2001	University of Chicago (Chicago, Illinois) ScientiæMagister in Computer Science
9/1995–6/1999	University of Chicago (Chicago, Illinois) Scientiæ Baccalaureus in Computer Science Artium Baccalaureus in Economics

1.C Academic Employment Background

6/2005–8/2007	Faculty Research Associate Institute for Advanced Computer Studies Department of Computer Science University of Maryland (College Park, Maryland)
8/2006–12/2006	Adjunct Professor Computer Science Department American University (Washington, DC)
6/2005–9/2006	Research Director Joint Institute for Knowledge Discovery (JIKD) University of Maryland (College Park, Maryland)
8/2001–5/2005	Research Assistant Department of Computer Science University of Maryland (College Park, Maryland)
8/2001–5/2005	Adjunct Lecturer Computer Science Department George Washington University (Washington, DC)
6/2001–5/2003	Adjunct Lecturer Computer Science Department Georgetown University (Washington, DC)
5/2002–8/2002	Adjunct Professor Advanced Physics Lab Johns Hopkins University (Laurel, Maryland)
8/2001–12/2001	Adjunct Lecturer Computer Science Department George Mason University (Fairfax, Virginia)
6/2000–9/2000	Visiting Graduate Mathematics and Computer Science Division Futures Laboratory Argonne National Laboratory (Argonne, Illinois)
6/1999–6/2001	Lecturer Computer Science Department University of Chicago (Chicago, Illinois)

2 Research, Scholarly, and Creative Activities

- In all references, my name is in **bold**.
- Unless otherwise indicated, the first author is the lead author.
- Underlined names indicate students with whom I collaborated—this includes students for whom I am/was the (co-)advisor and other students where the collaboration was limited to specific projects.
- For work in which a student took the lead, it is customary for the student to be first author, followed by faculty who have played an advisory or mentoring role, followed by other individuals who have contributed. In cases where a student is listed as the first author, a wavy underline indicates colleagues with whom I shared this advisory or mentoring role (to the extent of my knowledge).
- References marked with ^α indicate that authors are listed in alphabetical order, or that all co-authors contributed equally.

2.A Books

2.A.i Books Authored

- B1. **Jennifer Golbeck and Stacey Colino**. November 2023 The Purest Bond: Understanding the Human-Canine Connection. Simon & Schuster
- B2. **Jennifer Golbeck**. January 2015. Introduction to Social Media Investigation: A Hands On Approach. Syngress.
- B3. **Jennifer Golbeck**. 2013. Analyzing the Social Web. Burlington, MA: Morgan Kaufmann.
- B4. **Jennifer Golbeck**. 2008. Trust on the World Wide Web: A Survey. Hanover, MA: Now Publishers Inc.
- B5. **Jennifer Golbeck**. 2005. Art Theory for Web Design. Boston, MA: Addison-Wesley.

2.A.ii Books Edited

- B6. **Jennifer Golbeck (ed)**. 2018. Online Harassment, London, UK: Springer.
- B7. **Jennifer Golbeck (ed)**. 2008. Computing with Social Trust, London, UK: Springer.
- B8. K. Aberer, K.-S.Choi, N. Noy, D. Allemang, K.-I. Lee, L. Nixon, **Jennifer Golbeck**, P. Mika, D. Maynard, R. Mizoguchi, G. Schreiber, P. Cudré-Mauroux(Eds.) The Semantic Web – 6th International Semantic Web Conference, 2nd Asian Semantic Web Conference (proceedings), Lecture Notes in Computer Science, Vol. 4825, November 2007.

2.A.iii Chapters in Books

- BC1. **Jennifer Golbeck**. 2017. “Social Networking” in Wiley Handbook of Human-Computer Interaction, Kent Norman (ed.). Sterling.

- BC2. **Jennifer Golbeck**. 2015. "The Force of Relationships: Tie Strength in Star Wars" in *Star Wars Psychology: Dark Side of the Mind*, Travis Langley (ed.). Sterling.
- BC3. **Jennifer Golbeck**. 2015. "Who Needs an Untrustworthy Doctor? Maslow's Hierarchy of Needs" in *The Walking Dead Psychology: Psych of the Living Dead*, Travis Langley (ed.). Sterling.
- BC4. Ziegler, Cai-Nicolas, and **Jennifer Golbeck**. "Models for Trust Inference in Social Networks." *Propagation Phenomena in Real World Networks*. Springer International Publishing, 2015. 53-89.
- BC5. **Jennifer Golbeck**, Ugur Kuter. 2008. "The Ripple Effect: Change in Trust and Its Impact over a Social Network" in *Computing with Social Trust*. **Jennifer Golbeck** (ed.). Springer.
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- BC10. **Jennifer Golbeck**, 2004. "Getting Friendly with FOAFBot" in Paul Mutton, IRC Hacks, 2004. O'Reilly Associates: Cambridge, MA.
- BC11. **Jennifer Golbeck**, 2004. "Interrogate Trust Networks with TrustBot" in Paul Mutton, IRC Hacks, 2004. O'Reilly Associates: Cambridge, MA.
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- BC13. **Jennifer Golbeck**, 2004. "Convert Currency" in Paul Mutton, IRC Hacks, 2004. O'Reilly Associates: Cambridge, MA.
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- BC16. **Jennifer Golbeck**, Amy Alford, Ron Alford, James Hendler, 2004. "Organization and Structure of Information using Semantic Web Technologies," in *Handbook of Human Factors in Web Design*, Robert W. Proctor and Kim-Phuong L. Vu (eds.). Lawrence Erlbaum Associates, NJ.

2.B Articles in Refereed Journals¹

- J1. **Jennifer Golbeck**. Photo aesthetics as a factor in trust and interest assessments. *First Monday*, May, 2023
- J2. Dritjon Gruda, Dimitra Karanatsiou, Paul Hanges, **Jennifer Golbeck**, and Athena Vakali. Dont go chasing narcissists: A relational-based and multiverse perspective on leader narcissism and follower engagement using a machine learning approach. *Personality and Social Psychology Bulletin*, page 01461672221094976, 2022
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- J8. **Golbeck, Jennifer**. “Data We TrustBut What Data?.” *Reference & User Services Quarterly* 57.3 (2018): 196-199. 0.65
- J9. **Jennifer Golbeck, Summer Ash, Nicole Cabrera**. Hashtags as Online Communities with Social Support: A Study of Anti-Sexism-in-Science Hashtag Movements. *First Monday*, September, 2017. 1.47
- J10. **Jennifer Golbeck**, Jeff Gerhard, Farrah O’Colman, Ryan O’Colman. Scaling Up Integrated Structural and Content-Based Network Analysis. *Information Systems Frontiers* (2017). 1.450
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- J12. **Jennifer Golbeck**, Carman Neustaedter. Environmental Factors Affecting Where People Geocache. *Future Internet*, 8(2), 9. 2016. 0.789
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- J18. **Jennifer Golbeck** and Derek Hansen. A Method for Computing Political Preference Among Twitter Followers. *Social Networks*. 36: 20 pages, 2014. 4.059
- J19. Rebecca LaPlante, Judith Klavans, **Jennifer Golbeck**. Subject Matter Categorization of Tags Applied to Digital Images from Art Museums *Journal of the American Society for Information Science and Technology*. 23 pages, 2014. 2.137
- J20. Awalin Sopan, Manuel Freire, Meirav Taieb-Maimon, Catherine Plaisant, **Jennifer Golbeck**, and Ben Shneiderman. Exploring Data Distributions: Visual Design and Evaluation *International Journal of Human-Computer Interaction*, 29(2), 27 pages, 2013 0.943
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- J28. **Jennifer Golbeck** and Christian Halaschek-Wiener. Trust-Based Revision for Expressive Web Syndication. *Journal of Logic and Computation*. 19, 5 (October 2009), 771-790. 0.821
- J29. **Jennifer Golbeck**. Trust and Nuanced Profile Similarity in Online Social Networks. *ACM Transactions on the Web*, 3, 4, Article 12, 33 pages, 2009. 2.810

- J30. **Jennifer Golbeck**. 2008. Weaving a Web of Trust. *Science* 19 September 2008: 1640–1641. 29.78
- J31. James Hendler, **Jennifer Golbeck**. Metcalfe’s Law Applies to Web 2.0 and the Semantic Web. *Journal of Web Semantics*. 6(1): 14–20, 2008. 3.410
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- J36. Richard J. Williams, Neo Martinez, **Jennifer Golbeck**. Ontologies for Ecoinformatics, *Journal of Web Semantics*, 4(4): 237–242, 2006. 3.410
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- J41. P. Domingos, **J. Golbeck**, P. Mika, A. Nowak. Trends & Controversies: Social Networks and Intelligent Systems. *IEEE Intelligent Systems*, 20(1): 80 – 93, 2005. 1.438
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- J43. Aditya Kalyanpur, **Jennifer Golbeck**, Jay Banerjee, James Hendler. OWL: Capturing semantic information using a standardized web ontology language. *Multilingual Computing & Technology*, 15(7): 8 pages, 2004.
- J44. Leslie E. Chipman, Benjamin B. Bederson, **Jennifer Golbeck**. SlideBar: Analysis of a linear input device. *Behaviour and Information Technology*, 23(1): 1–9, 2004. 1.028
- J45. **Jennifer Golbeck**, Gilberto Fragoso, Frank Hartel, Jim Hendler, Jim Oberthaler, Bijan Parsia. The National Cancer Institute’s Thesaurus and Ontology. *Journal of Web Semantics*, 1(1): 75–80, 2004. 3.410

2.C Monographs, Reports, and Extension Publications

- R1. Aditya Kalyanpur, James Hendler, Bijan Parsia, **Jennifer Golbeck**. SMORE-semantic markup, ontology, and RDF editor. 2006.
- R2. **Jennifer Golbeck**. Computing and Applying Trust in Web-based Social Networks, Ph.D. Thesis, University of Maryland, College Park, 2005.
- R3. **Jennifer Golbeck**. Genetic Algorithms for Strategic Optimization. Master's Thesis, University of Chicago, 2001.

2.D Book Reviews, Other Articles, and Notes

- O1. "Digital Spaces and Their Perils"
Science, September 2022
- O2. "Off the Edge: Flat Earthers, Conspiracy Culture, and Why People Will Believe Anything"
Science, February 2022
- O3. "Breaking the Social Media Prism: How to Make Our Platforms Less Polarizing"
Science, April 2021
- O4. "In real life: a Review of Laurence Scott's The Four-Dimensional Human Ways of Being in the Digital World"
Science, August 12, 2016
- O5. "Data Meets Design: a Review of Judith Donath's The Social Machine"
Science, January 15, 2015
- O6. "The Live-Tweeted Prostitution Sting Was a Total Bust, and Not in a Good Way"
Slate, May 7, 2014
- O7. "What a Toilet Hoax Can Tell Us About the Future of Surveillance, on The Atlantic"
The Atlantic, April 29, 2014
- O8. "Google Tweaked How It Displays Search Results. Here's How to Change It Back"
Slate, March 14, 2014
Slate, January 1, 2014
- O9. "Beacon, ShopKick: Privacy Policies for location-tracking apps aren't clear enough"
Slate January 28, 2014
- O10. "Facebook Cleansing: How to delete all of your account activity"
Slate, January 1, 2014
- O11. "Facebook self-censorship: What happens to the posts you don't publish"
Slate, December 13, 2013
- O12. "Lovely Spam! Wonderful Spam! (book review of Spam A Shadow History of the Internet)"
Science: Vol. 340 no. 6137 p. 1171, 7 June 2013

2.E Talks, Abstracts, and Other Professional Papers Presented

2.E.i Invited Talks: Keynote (and Similar) Addresses

2.E.i.1 Academic Keynotes

- T1. “Personal Data, Privacy, and the (Semantic) Web”
International Semantic Web Conference (ISWC)
Monterey, California (November 2018)
- T2. “User Behavior and Intelligent Insights”
ACM Conference on Intelligent User Interfaces (IUI)
Tokyo, Japan (March 2018)
- T3. “Personalization, Privacy, and Peril?”
International Conference on Social Informatics
Oxford, UK (September 13, 2017)
- T4. “Ill be watching you: policing the line between personalization and privacy”
Alan Turing Institute
London, UK (September 12, 2017)
- T5. “Foretold Futures from Digital Footprints: Artificial Intelligence, Behavior Prediction, and Privacy”
ACM Conference on User Modeling, Adaptation and Personalization
Bratislava, Slovakia (July 12, 2017)
- T6. “The Psychological Science of Web Harassment”
9th International ACM Web Science Conference
Troy, NY (June 27, 2017)
- T7. “Trust and Social Media”
AAAI 2013 Fall Symposium Series
Arlington, VA (November 15-17, 2013)
- T8. “User Profiling: a two-sided argument”
Conference on Social Computing and Its Applications
Karlsruhe, Germany (October 2, 2013)
- T9. “Computing with Social Trust: Web Algorithms, Social Networks, and Recommendations”
Haverford College Distinguished Visitors Program, and Fantastic Lectures in Computer Science Series
Haverford, Pennsylvania (March 17, 2009)
- T10. “Social Recommender Systems”
SONIC and NICO Lecture Series, Northwestern University
Evanston, Illinois (November 12, 2008)
- T11. “The Dynamics of Web-based Social Networks: Membership, Relationships, and Change”
International Sunbelt Social Networking Conference (Sunbelt XXVIII)
St. Pete, Florida (January 22, 2008)

- T12. “Social Networks, the Semantic Web, and the Future of Online Scientific Collaboration”
FermiLab Colloquium Lecture
Batavia, Illinois (October 25 2006)
- T13. “Trust and Web Policy Systems”
Second International Workshop on the Value of Security through Collaboration
Baltimore, Maryland (September 1, 2006)

2.E.i.2 Non-Academic Keynotes

- T14. Baltimore Sun’s Women to Watch, Baltimore, MD (October 2022)
- T15. National Association of Corporate Directors, Washington, DC (October 2022)
- T16. LL Global, Orlando, FL (June 2022)
- T17. Customer Strategy Alliance, virtual (May 2022)
- T18. Worcester Economic Club, Worcester, MA (March 2022)
- T19. TEDxMarin, virtual (September 2021)
- T20. TEDxYouth, Austin, TX (February 8, 2020)
- T21. Texas REALTORS Winter Meeting, Austin, TX (February 7, 2020)
- T22. National Association of Independent Life Brokerage Agencies Annual Conference, Gaylord, TX (November 8, 2019)
- T23. Deloitte TMT Industry Forum Phoenix, AZ (October 14, 2019)
- T24. SPEAENCE f/s/t EDAILY, Seoul, South Korea (October 10, 2019)
- T25. CIBC Wood Gundy Eastern Institutional Investor Conference, Montreal, Quebec (September 25, 2019)
- T26. Florida Realtor Annual Convention, Orlando, FL (August 22, 2019)
- T27. 2019 Odessa Event, Philadelphia, PA (August 13, 2019)
- T28. National Association of Realtors Real Estate Broker Event, Portland, OR (June 27, 2019)
- T29. American Society of Association Executives Marketing, Membership & Communications Conference, Washington, DC (June 07, 2019)
- T30. Big Ten Plus , College Park, MD (June 18, 2019)
- T31. CIBC Wood Gundy 2019 Presidents Council Conference, Boston, MA (May 27, 2019)
- T32. J.P. Morgan Chase CTC Academy LIVE, Jersey City, NJ (May 23, 2019)
- T33. Fidelity Benefits Symposium, Scottsdale, AZ (May 21, 2019)
- T34. Girls E-Mentorship Innovation, Toronto, Ontario (May 7, 2019)

- T35. J.P. Morgan Chase CTC Academy LIVE, Wilmington, Delaware (May 2, 2019)
- T36. American Association of Colleges of Osteopathic Medicine Annual Meeting, Washington, DC (April 12, 2019)
- T37. J.P. Morgan Chase CTC Academy LIVE, Houston, TX (April 10, 2019)
- T38. National Association of Realtors 2019 REALTORS Broker Summit, Austin, TX (April 3, 2019)
- T39. J.P. Morgan Chase CTC Academy LIVE, Columbus, OH (March 21, 2019)
- T40. CGI Group Momentum Day, Arlington, VA (December 12, 2018)
- T41. John Hancock Financial , Boston, MA (November 15, 2018)
- T42. National Association of Personal Financial Advisors (NAPFA) , Philadelphia, PA (October 16, 2018)
- T43. J.P. Morgan Chase CTC Academy LIVE, New York, NY (September 27, 2018)
- T44. Morgan Stanley, New York, NY (September 26, 2018)
- T45. Association of Washington Business Policy Summit, Seattle, WA (September 19, 2018)
- T46. Financial Industry Regulatory Authority (FINRA), Rockville, MD (September 12, 2018)
- T47. National Association of REALTORS Broker's Edge, Hollywood, FL (August 28, 2018)
- T48. Raddon CEO Forum, Newport Coast, CA (August 7, 2018)
- T49. J.P. Morgan Chase CTC Academy LIVE, Tampa, FL (July 18, 2018)
- T50. FSI Forum, Las Vegas, NV (June 19, 2018)
- T51. Deloitte TMT Event 2018, San Carlos, CA (May 28, 2018)
- T52. T. Rowe Price Forum, Amelia Island, FL (May 8-9, 2018)
- T53. LESI 2018 Annual Conference, San Diego, CA (May 1, 2018)
- T54. Institutional Investor Conferences, Chicago, IL (April 18, 2018)
- T55. AAA/CAA Eastern Conference, Palm Beach, FL (March 26, 2018)
- T56. CASE Drive Conference, Bellevue, WA (February 27, 2018)
- T57. Cetera Premier Client Division Meeting, Dallas, TX (November 9, 2017)
- T58. Raddon Research Conference, Chicago, IL (November 6, 2017)
- T59. 21st Annual Healthcare Internet Conference, Austin, TX (October 24, 2017)
- T60. Wisconsin Governor's Cyber Security Summit, Madison, WI (October 16, 2017)
- T61. Campus Technology Conference, Chicago, IL (July 18, 2017)
- T62. Florida Public Pension Trustee Conference, Orlando, FL (June 28, 2017)

- T63. Financial Technology Forum, Chicago, IL (June 15, 2017)
- T64. National Association of Insurance Commissioners Conference, Kansas City, MO (May 24, 2017)
- T65. FedEx Security Awareness Meeting, Grapevine, TX (April 18, 2017)
- T66. Association of Home Office Underwriters Annual Meeting, San Diego, CA (April 3, 2017)
- T67. Wisconsin Governor's Conference on Tourism (Keynote), Milwaukee, WI (March 15, 2017)
- T68. Meeting Professionals International Conference (Keynote), Washington, DC (February 23, 2017)
- T69. Virginia Foundation for the Humanities edUi Conference, Charlottesville, VA (October 27, 2016)
- T70. Association for Financial Professionals Conference (Keynote), Orlando, FL (October 24, 2016)
- T71. State Library Resource Center Conference, Baltimore, MD (October 19, 2016)
- T72. Food Marketing Institute (Keynote), Tucson, AZ (March 16, 2016)
- T73. FedEx Cybersecurity Month (Keynote), Memphis, TN (October 4, 2016)
- T74. ZS Commercial Operations, Analytics & Technology Leadership Summit (Keynote), Philadelphia, PA (September 29, 2016)
- T75. Northrop Grumman Leadership of the Communications Organization, Washington, DC (June 17, 2016)
- T76. ISC2 SecureGov Conference (Keynote), Washington, DC (May 19, 2016)
- T77. ICI Mutual Insurance 2016 Annual Risk Management Confernece, New Orleans, LA (April 7, 2016)
- T78. Alliance for Continuing Education in the Health Professions Annual Conference, Dallas, TX (January 14, 2015)
- T79. Choice Hotels Owners Council (Keynote), Orlando, FL (February 4, 2016)
- T80. Maryland Association of Public Library Administrators Annual Meeting (Keynote), Ellicott City, MD (January 28, 2016)
- T81. HIMSS Privacy Forum (Keynote), Boston, MA (December 1, 2015)
- T82. Learning 2015 (Keynote), Orlando, FL (November 2, 2015)
- T83. Time Warner Security Summit (Keynote), Santa Monica, CA (September 10, 2015)
- T84. Talent Acquisition Program Management Conference (Keynote), Reston, VA (August 19, 2015)
- T85. Ingram Micro Vantage Denver (Keynote), Denver, CO (August 18, 2015)
- T86. Association of Executive Search Consultants (Keynote), New York, NY (April 15, 2015)
- T87. Ingram Micro Vantage Kansas City, Kansas City, MO (February 16, 2015)

- T88. Alliance for Continuing Education in the Health Professions (Keynote), Dallas, TX (January 14, 2014)
- T89. University Professional and Continuing Education Association (Keynote), Atlanta, GA (November 11, 2014)
- T90. Baltimore Data Day, Federal Reserve Bank of Richmond (Keynote), Baltimore, MD (July 11, 2013)
- T91. Data Science DC, Washington, DC (March 28, 2013)

2.E.ii Refereed conference proceedings

2.E.ii.1 Papers at Top-Tier Conferences ¹

- C1. Auxier, Brooke, Cody Buntain, Paul Jaeger, **Jennifer Golbeck**, Hernisa Kacorri. “#HandsOffMyADA: A Twitter Response to the ADA Education and Reform Act.” *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, 2019.
- C2. **Jennifer Golbeck** and Cody Buntain. “This Paper Is About Lexical Propagation on Twitter. H*ckin smart. 12/10. Would accept!”. *Proceedings of Advances in Social Network Analysis and Mining (ASONAM 2018)*. Barcelona, Spain.
- C3. Yue Zhang, Arti Ramesh, **Jennifer Golbeck**, Dhanya Sridhar and Lise Getoor. “A Structured Approach to Understanding Recovery and Relapse in AA”. *Proceedings of The Web Conference (WWW2018)*. Lyon, France.
- C4. Cody Buntain, McGrath, E., **Golbeck, J.**, and LaFree, G. Comparing Social Media and Traditional Surveys around the Boston Marathon Bombing. *#Microposts* (pp. 34-41), 2016
- C5. Peixin Gao, Hui Mao, John S. Baras, **Jennifer Golbeck** “STAR: Semiring Trust Inference for Trust-Aware Social Recommenders” *Proceedings of the ACM Conference on Recommender Systems (RecSys 2016)*, 10 pages, Boston, MA
- C6. Kan-Leung Cheng and I Zuckerman and D Nau, and **J Golbeck** “Predicting Agents’ Behavior by Measuring their Social Preferences.” *Proceedings on the European Conference on Artificial Intelligence*. 2014, 10 pages, Prague, Czechia.
- C7. Tammar Shrot, Avi Rosenfeld, **Jennifer Golbeck**, Sarit Kraus. Timing Interruptions to Improve User Performance. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI’14)*. 10 pages. April 2014, Toronto, Canada 23%
- C8. **Jennifer Golbeck**, Eric Norris. Personality, Movie Preferences, and Recommendations. In *Proceedings of the International Conference on Advances in Social Network Analysis and Mining*, 4 pages. August 2013, Niagra Falls, Canada. 15%
- C9. Bert Huang, Angelika Kimmig and Lise Getoor and **Jennifer Golbeck**. Flexible Framework for Probabilistic Models of Social Trust. In *2013 Conference on Social Computing, Behavioral Modeling and Prediction*, 9 pages. April 2013, College Park, MD 31%

¹Conferences with highly-selective acceptance rates and/or top reputations in their field.

- C10. Carman Neustaedter and **Jennifer Golbeck**. Exploring pet video chat: the remote awareness and interaction needs of families with dogs and cats. In *Proceedings of Computer Supported Cooperative Work (CSCW'13)*, 2013, 6 pages. February 2013, San Antonio, TX
- C11. **Jennifer Golbeck**. The Twitter Mute Button: A Web Filtering Challenge. In *Proceedings of the 30th International Conference on Human Factors in Computing Systems (CHI '12)*, 23%
pages 2755–2758. May 2012, Austin, TX.
- C12. Irene Eleta and **Jennifer Golbeck**. A Study of Multilingual Social Tagging of Art Images: Cultural Bridges and Diversity. In *Proceedings of Computer Supported Cooperative Work (CSCW'12)*, pages 695–704. February 2012, Seattle, Washington 40%
- C13. Cheng, K.L., Zuckerman, I., Nau, D., and **Golbeck, J.** The Life Game: Cognitive Strategies for Repeated Stochastic Games. In *IEEE Third International Conference on and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, pages 495–502. 10%
October 2011, Boston, Massachusetts.
- C14. Nicholas Violi, **Jennifer Golbeck**, Kan-leung Cheng, and Ugur Kuter. Caretaker: A Social Game for Studying Trust Dynamics. In *IEEE Third International Conference on and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, pages 451–456. October 2011, Boston, Massachusetts. 10%
- C15. **J. Golbeck**, C. Robles, M. Edmondson, and K. Turner. Predicting personality from twitter. In *IEEE Third International Conference on and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, pages 149–156. October 2011, Boston, Massachusetts. 10%
- C16. K.L. Cheng, U. Kuter, and **J. Golbeck**. Coevolving strategies in social-elimination games. In *IEEE Third International Conference on and 2011 IEEE Third International Conference on Social Computing (SocialCom)*, pages 118–126. October 2011, Boston, Massachusetts. 10%
- C17. Thomas Dubois, **Jennifer Golbeck**, and Aravind Srinivasan. Network Clustering Approximation Algorithm Using One Pass Black Box Sampling. In *Third IEEE International Conference on Social Computing (SocialCom)*, pages 418–424. October 2011, Boston, Massachusetts. (Best Paper Award). 10%
- C18. Thomas Dubois, **Jennifer Golbeck**, and Aravind Srinivasan. Predicting Trust and Distrust in Social Networks. In *Third IEEE International Conference on Social Computing (SocialCom)*, pages 418–424. October 2011, Boston, Massachusetts. 10%
- C19. **Jennifer Golbeck** and Derek Hansen. Computing Political Preference Among Twitter Followers. In *Proceedings of the 29th International Conference on Human Factors in Computing Systems (CHI '11)*, pages 1105–1108. April 2011, Vancouver, Canada. 23%
- C20. Greg Walsh and **Jennifer Golbeck** Curator: a game with a purpose for collection recommendation. In *Proceedings of the 28th international Conference on Human Factors in Computing Systems (CHI '10)*, pages 2079–2082. April 2010, Atlanta, Georgia. 22%
- C21. Freire, M., Plaisant, C., Shneiderman, B., and **Golbeck, J.** ManyNets: an interface for multiple network analysis and visualization. In *Proceedings of the 28th international Conference on Human Factors in Computing Systems (CHI '10)*, pages 213–222. Atlanta, Georgia, USA, April 10–15, 2010. 22%
- C22. Ugur Kuter, **Jennifer Golbeck**^α. Semantic Web Service Composition in Social Environments. *Proceedings of the International Semantic Web Conference (ISWC'09)*, pages 344–358. November 2009, Washington, D.C. (Best Paper Award) 20%

- C23. Thomas DuBois, **Jennifer Golbeck**, Aravind Srinivasan. Rigorous Probabilistic Trust Inference with applications to clustering. *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence*, pages 655–658. September 2009, Milan Italy. 18%
- C24. Derek Hansen, **Jennifer Golbeck**. Mixing it Up: Recommending Collections of Items. *Proceedings of the Conference on Human Factors in Computing Systems (CHI'09)*, pages 1217–1226. April 2009, Boston, Massachusetts. 24.5%
- C25. **Jennifer Golbeck**, Matthew Rothstein. Linking Social Networks on the Web with FOAF: A Semantic Web Case Study. *Proceedings of the Twenty-Third National Conference on Artificial Intelligence (AAAI-08)*, pages 1138–1143. July 2008, Chicago, Illinois. 24%
- C26. Ugur Kuter and **Jennifer Golbeck**^α. SUNNY: A New Algorithm for Trust Inference in Social Networks, using Probabilistic Confidence Models. *Proceedings of the Twenty-Second National Conference on Artificial Intelligence (AAAI-07)*, pages 1377–1382. July 2007, Vancouver, Canada. 27%
- C27. Yarden Katz and **Jennifer Golbeck**. Social Network-based Trust in Prioritized Default Logic. *Proceedings of The Twenty-First National Conference on Artificial Intelligence (AAAI-06)*, pages 1345–1350. July 2006, Boston, Massachusetts. 30%
- C28. **Jennifer Golbeck**, James Hendler. Inferring reputation on the semantic web. *Proceedings of the 13th International World Wide Web Conference*, 8 pages. May 2004. New York, NY. 14.6%
- C29. **Jennifer Golbeck**, Michael Grove, Bijan Parsia, Aditya Kalyanpur, and James Hendler. New Tools for the Semantic Web, *Proceedings of the 13th International Conference on Knowledge Engineering and Knowledge Management (EKAW 2002)*, pages 392–400. October 2002, Sigüenza, Spain. 34%

2.E.ii.2 Papers at Other Conferences

- C30. Dritjon Gruda, Dimitra Karanatsiou, Paul Hanges, **Jennifer Golbeck**, Athena Vakali. “Leader Narcissism and Follower Engagement - A Machine Learning Approach” *81st Annual Meeting of the Academy of Management*. 2021
- C31. **Jennifer Golbeck**. “Dogs Good, Trump Bad: The Impact of Social Media Content on Sense of Well-Being.” *Proceedings of the 10th ACM Conference on Web Science*. ACM, 2019.
- C32. Brooke Auxier, **Jennifer Golbeck**, Cody Buntain. Analyzing sentiment and themes in fitness influencers Twitter dialogue *Proceedings of the 2019 iConference*. 2019
- C33. **Jennifer Golbeck**. Predicting Alcoholism Recovery from Twitter. *Proceedings of the 2018 International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SBP-BRiMS)*, 10 pages. 2018
- C34. Cody Buntain and **Jennifer Golbeck**. Automatically Identifying Fake News in Popular Twitter Threads. *Proceedings of The 2nd IEEE International Conference on Smart Cloud*, 10 pages. New York, NY, 2017 **Best Paper Award**
- C35. **Jennifer Golbeck**. The Importance of Consent in User Comfort with Personalization. *Proceedings of the 9th International Conference on Social Informatics (SocInfo 2017)*, 10 pages. 2017

- C36. Booke Auxier and **Jennifer Golbeck**. The President on Twitter: A Characterization Study of @realDonaldTrump. *Proceedings of the 9th International Conference on Social Informatics (SocInfo 2017)*, 10 pages. 2017
- C37. **Jennifer Golbeck**. User Concerns with Personal Routers Used as Public Wi-fi Hotspots. *Proceedings of the IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, 8 pages. 2017
- C38. **Jennifer Golbeck**, Zahra Ashktorab, Rashad O. Banjo, Alexandra Berlinger, Siddharth Bhagwan, Cody Buntain, Paul Cheakalos, Alicia A. Geller, Qunit Gregory, Rajesh Kumar Gnanasekaran, Raja Rajan Gunasekaran, Kelly M. Hoffman, Jenny Hottle, Vichita Jienjittlert, Shivika Khare, Ryan Lau, Marianna J. Martindale, Shalmali Naik, Heather L. Nixon, Piyush Ramachandran, Kristine M. Rogers, Lisa Rogers, Meghna Sardana Sarin, Gaurav Shahane, Jayane Thanki, Priyanka Vengataraman, Zijian Wan and Derek Michael Wu. A Large Labeled Corpus for Online Harassment Research. *Proceedings of the 9th International ACM Web Science Conference*, pages 229-233. Troy, NY (2017)
- C39. Zahra Ashktorab, Eben Haber, **Jennifer Golbeck** and Jessica Vitak. Beyond Cyberbullying: Self-Disclosure, Harm and Social Support on ASKfm *Proceedings of the 9th International ACM Web Science Conference*, pages 3-12. Troy, NY, 2017
- C40. **Jennifer Golbeck**. Detecting Coping Style from Twitter, *Proceedings of the 8th International Conference on Social Informatics (SocInfo 2016)*, 10 pages. 2016
- C41. **Jennifer Golbeck**. User Privacy Concerns with Common Data Used in Recommender Systems, *Proceedings of the 8th International Conference on Social Informatics (SocInfo 2016)*, 9 pages. 2016
- C42. Cody Buntain, Jimmy Lin, and **Jennifer Golbeck**, Learning to Discover Key Moments in Social Media Streams, in *Proceedings of the IEEE Consumer Communications and Networking Conference*, 10 pages. 2016.
- C43. Gao, Peixin, John S. Baras, and Jennifer Golbeck. Semiring-based trust evaluation for information fusion in social network services. *Information Fusion (Fusion)*, 2015, pages 590-596. 2015.
- C44. Buntain, Cody, **Jennifer Golbeck**, and Gary LaFree. Powers and problems of integrating social media data with public health and safety. *Bloomberg Data for Good Exchange*, 8 pages. New York, NY, USA (2015).
- C45. Ashktorab, Zahra, S Kumar, S De, **J Golbeck**. iAnon: Leveraging social network big data to mitigate behavioral symptoms of cyberbullying. *iConference 2014 (Social Media Expo)*, 4 pages. 2014.
- C46. Cody Buntain and **Jennifer Golbeck**. Identifying social roles in reddit using network structure. *Proceedings of the 23rd international conference on World Wide Web Companion Volume*, pages 615-620. 2014.
- C47. Greg Walsh and **Jennifer Golbeck**. 2014. StepCity: a preliminary investigation of a personal informatics-based social game on behavior change. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems (CHI EA '14)*. ACM, New York, NY, USA, 2371-2376.
- C48. Sibel Adali and **Jennifer Golbeck**. Predicting personality with social behavior. In *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 8 pages. August 2012, Istanbul, Turkey.

- C49. Buntain, Cody, **Jennifer Golbeck**, Dana Nau, and Sarit Kraus. Advice and Trust in Games of Choice. In *Tenth Annual Conference on Privacy, Security and Trust*, 2 pages. July 2012, Paris, France.
- C50. **Jennifer Golbeck**, Hal Warren, and Eva Winer. Making trusted attribute assertions online with the publish trust framework. In *Tenth Annual Conference on Privacy, Security and Trust*, 2 pages. July 2012, Paris, France.
- C51. David Yates and **Jennifer Golbeck**. Is facebook appropriate for the classroom? a comparison of student and faculty perspectives. In *Proceedings of the Euro-American Conference for Academic Disciplines and Creativity*, 27 pages. June 2012, Prague, Czech Republic. (Outstanding Research Presentation).
- C52. **Jennifer Golbeck**. STEM initiatives for improved communication skills in the zombie apocalypse. In *Proceedings of the 2012 ACM Conference on Human Factors in Computing Systems Extended Abstracts*, pages 1425–1426. May 2012, Austin, TX.
- C53. **Jennifer Golbeck** and Carman Neustaedter. Pet video chat: monitoring and interacting with dogs over distance. In *Proceedings of the 2012 ACM Conference on Human Factors in Computing Systems Extended Abstracts*, pages 1425–1426. May 2012, Austin, TX.
- C54. **Jennifer Golbeck**, Cristina Robles, Karen Turner Predicting Personality with Social Media. *Proceedings of alt.chi, ACM Conference on Human Factors in Computing (CHI 2011)*, pages 253–262. April 2011, Vancouver, Canada.
- C55. James Michaelis, **Jennifer Golbeck**, James Hendler Leveraging the Semantic Web to Enable Content Mashup For End Users. *Proceedings of HCI International 2011*, 10 pages. July 2011, Orlando, Florida.
- C56. **Jennifer Golbeck**, Kenneth Fleischmann. Trust in Social Q &A: The Impact of Text and Photo Cues of Expertise. *Proceedings of ASIST 2010*, pages 1–10. October 2010, Pittsburgh, Pennsylvania.
- C57. Klavans, Judith, **Jennifer Golbeck**. Integrating Multiple Computational Techniques for Improving Image Access: Applications to Digital Collections. *Proceedings of the 2010 Grace Hopper Conference*, 5 pages. September 2010, Atlanta, Georgia.
- C58. Dana Rotman, **Jennifer Golbeck**, Jennifer Preece. The Community is Where the Rapport Is: On Sense and Structure in the YouTube Community. *2009 Communities & Technologies Conference*, pages 41–50. June, 2009. University Park, Pennsylvania.
- C59. **Jennifer Golbeck**. On the Internet, Everybody Knows You’re a Dog: The Human-Pet Relationship in Online Social Networks. *ACM Conference on Human Factors in Computing Systems Extended Abstracts*, pages 4495–4500. April 2009, Boston, Massachusetts.
- C60. **Jennifer Golbeck**, Michael Wasser. SocialBrowsing: Integrating Social Networks into Web Browsing. *ACM Conference on Human Factors in Computing Systems Extended Abstracts*, pages 2381–2386. April 2007, San Jose, California.
- C61. Aaron Mannes, **Jennifer Golbeck**. Ontology Building: A Terrorism Specialist’s Perspective. *Proceedings of the IEEE Aerospace Conference*, 5 pages. March 2007, Big Sky, Montana.
- C62. Aaron Mannes, **Jennifer Golbeck**. Building a Semantic Web Portal for Counterterror Analysis. *Proceedings of the IEEE Aerospace Conference*, 5 pages. March 2007, Big Sky, Montana.

- C63. **Jennifer Golbeck**, Computing with Trust: Definition, Properties, and Algorithms. *Proceedings of International Conference on Security and Privacy in Communication Networks*, pages 1-7. August 2006, Baltimore, Maryland.
- C64. **Jennifer Golbeck**. Generating Predictive Movie Recommendations from Trust in Social Networks. *Proceedings of the Fourth International Conference on Trust Management*, pages 93–104. May 2006, Pisa, Italy.
- C65. **Jennifer Golbeck**, James Hendler. FilmTrust: Movie recommendations using trust in web-based social networks. *Proceedings of the IEEE Consumer Communications and Networking Conference*, pages 497–529. January 2006, Las Vegas, Nevada.
- C66. **Jennifer Golbeck**, Bernardo Cuenca Grau, Christian Halaschek-Wiener, Aditya Kalyanpur, Yarden Katz, Bijan Parsia, Andrew Schain, Evren Sirin, and James Hendler. Semantic web research trends and directions. *Proceedings of the First international Conference on Pattern Recognition and Machine Intelligence, PReMI. 2005*, pages 160-169. December 2005, Kolkata, India.
- C67. **Jennifer Golbeck**, James Hendler. Accuracy of Metrics for Inferring Trust and Reputation in Semantic Web-based Social Networks, *Proceedings of 14th International Conference on Knowledge Engineering and Knowledge Management*, pages 116–131. October 2004, Northamptonshire, UK.
- C68. **Jennifer Golbeck**, James Hendler. Reputation Network Analysis for Email Filtering. *Proceedings of the First Conference on Email and Anti-Spam*, pages 54–58. July 2004, Mountain View, California.
- C69. **Jennifer Golbeck**, Bijan Parsia, James Hendler. Trust Networks on the Semantic Web, *Proceedings of Cooperative Information Agents*, pages 238–249. August 2003, Helsinki, Finland.
- C70. Mutton, Paul and **Jennifer Golbeck**. Visualization of Semantic Metadata and Ontologies, *Proceedings of Information Visualization*, pages 300–305. July 2003, London, UK.
- C71. Kalyanpur, Aditya and **Jennifer Golbeck** and Michael Grove and Jim Hendler. 2002. An RDF Editor and Portal for the Semantic Web, *Proceedings of Semantic Authoring, Annotation & Knowledge Markup (ECAI 2002)*, 4 pages. July 2002, Lyon, France.
- C72. **Jennifer Golbeck**. Evolving Strategies for the Prisoner’s Dilemma, *Advances in Intelligent Systems, Fuzzy Systems, and Evolutionary Computation*, pages 299–306. February 2002, Interlaken, Switzerland.

2.E.iii.3 Papers at Refereed Workshops

- W1. **Jennifer Golbeck** and Simon Li. A Dataset and Analysis of Bias. *The Who Are You?! Adventures in Authentication Workshop (WAY 2020)*, 2020
- W2. **Jennifer Golbeck**. Improving Emotional Well-Being on Social Media with Collaborative Filtering. *Personalisation and Community*, 2020.
- W3. Abigail Bickford, Cody Buntain, **Jennifer Golbeck**, Sean Mussenden, Pal Doshi, Shiyun Chen, Tracy Zeeger, Sydney Vaile, Rebecca L Annis, Pushkar Deshpande, Jency Francis, Ruchira Kapoor, Gwen Hambright, Himanshu Sawant, Etienne Nadeau, Shivam Saith, Naveen Krishnamurthi, Xinyun Zhang. 2018. Identifying Stance in Controversial Topics Through

Textual, Social, and Emotional Dimensions. *Proceedings of the 2018 Beyond Online Data workshop at the International Conference on Weblogs and Social Media*.

- W4. Auxier, Brooke, and **Jennifer Golbeck**. The Challenge of Personal Attribute Preferences in Recommending Diverse, Reliable News Sources. *CIKM Workshops*. 2018.
- W5. Cody Buntain, Erin McGrath, **Jennifer Golbeck**, and Gary LaFree, Comparing Social Media and Traditional Surveys Around the Boston Marathon Bombing, in *6th Workshop on Making Sense of Microposts (#Microposts2016)*, 2016.
- W6. Belov, Nadya, J Schlachter, C Buntain, **J. Golbeck**. Computational trust assessment of open media data. *2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, . IEEE, 2013.
- W7. **Jennifer Golbeck**, Thameem Khan, Nilay Sanghavi and Nishita Thakker. Multiple Personalities on the Web: A Study of Shared Mboxes in FOAF. *Proceedings of the 2009 Workshop on Social Data on the Web*, 12 pages. October 2009, Washington, DC.
- W8. Thomas DuBois, **Jennifer Golbeck**, John Kleint, Aravind Srinivasan. Improving Recommendation Accuracy by Clustering Social Networks with Trust. *Proceedings of the ACM Rec-Sys 2009 Workshop on Recommender Systems and the Social Web*, 8 pages. October 2009, New York, New York.
- W9. Audun Josang, **Jennifer Golbeck**, Challenges for robust trust and reputation systems. *Proceedings of the 5th International Workshop on Security and Trust Management*. 12 pages. August, 2009, Saint Malo, France.
- W10. Elena Zheleva, **Jennifer Golbeck**, Lise Getoor, Ugur Kuter. Using Friendship Ties and Family Circles for Link Prediction. *SNA-KDD Workshop on Social Network Mining and Analysis*, pages 97-113. August 2008, Las Vegas, Nevada.
- W11. V. Shiv Naga Prasad, Behjat Siddiquie, **Jennifer Golbeck**, and Larry S. Davis. Classifying Computer Generated Charts. In *Proceedings of the Workshop on Content Based Multimedia Indexing*, pages 85-92. June 2007, Bordeaux, France.
- W12. **Jennifer Golbeck**, Aaron Mannes. Using Trust and Provenance for Content Filtering on the Semantic Web. *Proceedings of the Workshop on Models of Trust on the Web*, 9 pages. May 2006, Edinburgh, UK.
- W13. Christian Halaschek-Wiener, **Jennifer Golbeck**, Bijan Parsia, Vladimir Kolovski, and Jim Hendler. Image browsing and natural language paraphrases of semantic web annotations. *First International Workshop on Semantic Web Annotations for Multimedia (SWAMM)*, 12 pages. May 2006, Edinburgh, UK.
- W14. Christian Halaschek-Wiener, **Jennifer Golbeck**, Andrew Schain, Michael Grove, Bijan Parsia, and Jim Hendler. Annotation and provenance tracking in semantic web photo libraries. *Proceedings of the International Provenance and Annotation Workshop*, pages 82–89. May 2006, Chicago, Illinois.
- W15. **Jennifer Golbeck**. Combining Provenance with Trust in Social Networks for Semantic Web Content Filtering. *Proceedings of the International Provenance and Annotation Workshop*, pages 101–108. May 2006, Chicago, Illinois.

- W16. Yarden Katz and **Jennifer Golbeck**. Nonmonotonic Reasoning with Web-Based Social Networks. *Proceedings of the Workshop on Reasoning on the Web*, pages 469–475. May 2006, Edinburgh, UK.
- W17. Aaron Mannes, **Jennifer Golbeck**, James Hendler. Semantic Web and Target-Centric Intelligence: Building Flexible Systems that Foster Collaboration. *Proceedings of Workshop Intelligent User Interfaces for Intelligence Analysis*, 4 pages. January 2006, Sydney, Australia.
- W18. **Jennifer Golbeck**. Semantic Web Interaction through Trust Network Recommender Systems. *End User Semantic Web Interaction Workshop*, pages 327–339. November 2005, Sanibel Island, Florida.
- W19. **Jennifer Golbeck**. Personalizing Applications through Integration of Inferred Trust Values in Semantic Web-Based Social Networks. *Semantic Network Analysis Workshop*, pages 1005–1018. November 2005, Sanibel Island, Florida.
- W20. Bijan Parsia, Taowei Wang, and **Jennifer Golbeck**. Visualizing Web Ontologies with Crop-Circles. *End User Semantic Web Interaction Workshop*, pages 1–8. November 2005, Sanibel Island, Florida.
- W21. Christian Halaschek-Wiener, Andrew Schain, **Jennifer Golbeck**, Michael Grove, Bijan Parsia, Jim Hendler. A flexible approach for managing digital images on the semantic web. *5th International Workshop on Knowledge Markup and Semantic Annotation*, pages 49–58. November 2005, Galway, Ireland.
- W22. Kalyanpur, Aditya, Nada Hashmi, **Jennifer Golbeck**, Bijan Parsia. Lifecycle of a Casual Web Ontology Development Process. *Proceedings of the Workshop on Application Design, Development and Implementation Issues in the Semantic Web*, 8 pages. May 2004, New York, New York.
- W23. **Jennifer Golbeck**, Paul Mutton, Semantic Web Interaction on Internet Relay Chat, *Proceedings of Interaction Design on the Semantic Web*, 5 pages. May 2004, New York, New York.

2.E.iii.4 Refereed Posters²

- P1. Brooke Auxier and **Jennifer Golbeck**. Analyzing topic and stance in fake news stories. *2019 iConference*, 2019.
- P2. Cody Buntain, **Jennifer Golbeck**, B. Auxier, B. G. Assefa, K. Boyd, K. M. Byers, G. Chawla, D. Chen, B. J. Analyzing a Fake News Authorship Network. *2019 iConference*, 2019.
- P3. Cody Buntain and **Jennifer Golbeck**, Brooke Liu, Gary LaFree. Evaluating Public Response to the Boston Marathon Bombing and Other Acts of Terrorism Through Twitter. *International Conference on Weblogs and Social Media (ICWSM)*, April 2016, Cologne, Germany.
- P4. Marina Cascaes Cardoso, Elizabeth Warrick, **Jennifer Golbeck**, Jenny Preece. Motivational Impact of Facebook Posts on Environmental Communities. *The 19th ACM conference on Computer-Supported Cooperative Work and Social Computing (CSCW'16)*, March 2016, San Francisco, CA.

² Peer-reviewed poster presentations, typically accompanied by short descriptions in associated proceedings.

- P5. Irena Eleta and **Jennifer Golbeck**. Bridging Languages in Social Networks: How Multilingual Users of Twitter Connect Language Communities?, *ASIS&T 2012 Annual Meeting*, October 2012, Baltimore, Maryland.
- P6. Bert Huang and Angelika Kimmig and Lise Getoor and **Jennifer Golbeck**. Probabilistic Soft Logic for Trust Analysis in Social Networks, *International Workshop on Statistical Relational AI*. August 2012, Catalina Island, CA.
- P7. Cristina Robles, **Jennifer Golbeck**. Facebook Relationships in the Workplace. *Proceedings of CompleNet 2012*. March 2012, Marathon, Florida.
- P8. Judith L. Klayans, Susan Chun, **Jennifer Golbeck**, Dagobert Soergel, Robert Stein, Ed Bachta, Rebecca LaPlante, Kate Mayo, John Kleint. Language and Image: T3 = Text, Tags, and Trust. *2009 Digital Humanities Conference*. July 2009, College Park, Maryland.
- P9. **Jennifer Golbeck**, Jeanne Kramer-Smyth. Visualizing Archival Collections with ArchivesZ. *Proceedings of the 2009 Digital Humanities Conference*, July 2009, College Park, Maryland.
- P10. Praveen Paruchuri, Preetam Maloor, Bob Pokorny, Aaron Mannes, **Jennifer Golbeck**. Cultural Modeling in a Game-Theoretic Framework, *AAAI Fall Symposium on Adaptive Agents in Cultural Contexts*. November 2008, Washington, DC.
- P11. Wu, P. F., Qu, Y., Fleischmann, K., **Golbeck, J.**, Jaeger, P., Preece, J., & Shneiderman, B. Designing a Community-Based Emergency Communication System: Requirements and Implications. *Annual Meeting of the American Society for Information Science and Technology (ASIS&T 2008)*. October 2008, Columbus, OH.
- P12. **Jennifer Golbeck**, FilmTrust: Movie Recommendations from Semantic Web-based Social Networks. *IEEE Consumer Communications and Networking Conference*. January 2006, Las Vegas, Nevada.
- P13. **Jennifer Golbeck**, FilmTrust: Movie Recommendations from Semantic Web-based Social Networks. *International Semantic Web Conference*. November 2005, Galway, Ireland
- P14. Halaschek-Wiener, Christian , Jennifer Golbeck, Andrew Schain, Michael Grove, Bijan Parsia, Jim Hendler Photostuff-an image annotation tool for the semantic web. *Proceedings of the Poster Track, 4th International Semantic Web Conference*. November 2005, Galway, Ireland.
- P15. Pin Xu, Lyubov Remennik, N. Rao Thotakura, **Jennifer Golbeck**, Liju Fan. Prototype development of an immunology ontology that integrates multiple biomedical ontologies. *7th International Protege Conference*. July 2004, Washington, DC.
- P16. **Jennifer Golbeck**, Bijan Parsia, James Hendler. Trust Networks on the Semantic Web. *Twelfth International World Wide Web Conference*, May 2003, Budapest, Hungary.
- P17. **Jennifer Golbeck**, Ron Alford, Ross Baker, Mike Grove, Jim Hendler, Aditya Kalyanpur, Amy Loomis, Ron Reck. Semantic Web Tools from MINDSWAP. *1st Annual International Semantic Web Conference*, June 2002, Sardinia, Italy.

2.I Contracts and Grants

Total funding to UMD is \$10,902,834 (my share \$3,722,115) from 18 awards.

On awards where UMD was a subcontractor, I am listed as “UMD PI / co-PI” and the total award amount, the UMD share, and my share are listed.

On awards where I am listed as only “PI / co-PI”, UMD is the primary institution and there are no subcontracts. The full award amount and my share are listed.

2.I.i Pending Award Applications

PG1. **co-PI**: Semantic Foundations and Formal Methods for Evolutionary System-of-System Architectures

Sponsor: DoD Minerva

Total Award: \$990,000

Duration: 2023-2026

PG2. **PI**: E-VERIFY: STTR: PACT: Personalized Account and Community management Tool

Sponsor: Naval Air Warfare Center

Total Award: \$72,000

Duration: 2021

PG3. **co-PI**: Food & Agricultural Assurance &; Supply Chains Testbed (FAAST)

Sponsor: DARPA

Total Award: \$2,000,000

Duration: 2021

PG4. **PI**: SaTC Core: Detection, Filtering, and Analysis of Online Harassment

Sponsor: NSF

Total Award: \$498,934

Duration: 09/01/2018- 8/30/2022

PG5. **co-PI**: CPS: Frontier: Collaborative Research: Networked HCPS: Models, Architectures and Performance Evaluation

Sponsor: NSF

Total Award: \$5,999,568

Duration: 09/01/2019- 8/30/2022

2.I.ii Current and Past Awards

G1. **PI**, “Advanced Data Science”

Sponsor: National Security Agency

Total Award Amount: \$149,999

Duration: September 2018 - August 2019

- G2. **co-PI**, “INSPIRE Track 2: Computational Modeling of Grievance and Political Instability Through Global Media”
 Sponsor: NSF
 Total Award Amount: \$2,266,183
 My Share: \$320,000
 Duration: September 2014 - August 2018
- G3. **co-PI**, “Science of Security Lablet”
 Sponsor: National Security Agency
 Total Award Amount: \$4,737,089
 My Share: \$214,000
 Duration: September 2014 - March 2017
- G4. **PI**, “EAGER: Automated Content-Based Detection of Online Harassment”
 Sponsor: NSF
 Total Award Amount: \$150,000
 My Share: \$150,000
 Duration: July 2015 - December 2016
- G5. **Collaborator**, “NIDA NEWS: A New Paradigm for Drug Early Warning Systems”
 Sponson: NIH-National Institute on Drug Abuse
 Total Award Amount: \$855,389 My Share: \$164,055 Duration: July 2014 - August 2016
- G6. **UMD PI**, “Trust in Crowds”
 Sponsor: Office of Naval Research
 Total Award Amount: \$1,238,752.00
 UMD Award Amount: \$150,000
 My Share: \$150,000
 Duration: February 2012 – January 2015
- G7. **UMD co-PI**, “E-VERIFY: Learning and Predicting Ties in Social Networks”
 UMD PI: Aravind Srinivasan, UMD co-PI: Lise Getoor
 Sponsor: IARPA
 Total Award Amount: \$13,360,000
 UMD Award Amount: \$2,142,156
 My Share: \$71,000
 Duration: July 2012 – June 2015
- G8. **PI**, “Center for Network Science”
 Sponsor: Army Research Office
 Total Award Amount: \$157,000,000
 UMD Award Amount: \$1,200,000
 My Share: \$1,200,000
 Duration: September 2009 – August 2014
- G9. **UMD PI**, “Semantic Web Informatics for Species in Space and Time”

Sponsor: National Science Foundation
 Total Award Amount: \$1,502,798
 UMD Award Amount: \$178,590
 My Share: \$178,590
 Duration: January 2010 – January 2013

G10. **PI**, “Behavior Network Diagrams”

co-PI: Ugur Kuter
 Sponsor: National Geospatial Intelligence Agency
 Award Amount: \$750,000
 My Share: \$500,000
 Duration: September 2009 – August 2012

G11. **Co-PI**, “T3: Text, Tagging and Trust to Improve Image Access for Museums and Libraries”

PI: Judith Klavans
 Sponsor: Institute for Museum and Library Services
 Award Amount: \$996,750
 My Share: \$498,375
 Duration: September 2008 – August 2011

G12. **PI**, “EAGER: Understanding Social Behavior in Real-Time Strategy Games”

co-PI: Ugur Kuter
 Sponsor: National Science Foundation
 Award Amount: \$196,199
 My Share: \$98,100
 Duration: September 2009 – August 2011

G13. **PI**, “Grant for Workshop on Social Trust Computing”

Sponsor: Army Research Office
 Award Amount: \$25,000
 My Share: \$25,000
 Duration: July 2010 – July 2011

G14. **PI** “Rigorous Probabilistic Trust-inference with Applications to Social Network Analysis”

Sponsor: Army Research Office
 Award Amount: \$50,000
 My Share: \$50,000
 Duration: July 2010 – April 2011

G15. **co-PI**, “Expertise@Maryland University of Maryland”

PI: Doug Oard
 Sponsor: University of Maryland, Office of the Vice President for Research
 Award Amount: \$88,000
 My Share: \$58,000
 Duration: September 2007 – May 2009

G16. **co-PI**, “Workshop on Doctoral Education in the iSchools”

PI: Allison Druin, co-PI: Paul T. Jaeger
 Sponsor: National Science Foundation
 Award Amount: \$45,000

My Share: \$15,000

Duration: April 2008 – June 2008

G17. **PI**, “A Graphical Game Theoretic Asymmetric Tactic and Strategy Generation for Simulation and Training”

Sponsor: Office of Naval Research

Award Amount: \$30,000

My Share: \$30,000

Duration: July 2007 – February 2008

G18. **PI**, “ArchivesZ: Visualizing Archival Collections”

Sponsor: National Endowment for the Humanities

Award Amount: \$14,050

My Share: \$14,050

Duration: September 2008 – August 2009

G19. **PI**, “Trust in Open Networks”

Sponsor: DARPA

Total Award Amount: \$284,589

UMD Award Amount: \$50,000

My Share: \$50,000

Duration: January 2009 – September 2009

G20. **PI**, “Email Filtering with Trust”

Sponsor: Samsung Telecom America

Award Amount: \$100,000

My Share: \$100,000

Duration: December 2008 – November 2009

2.J Fellowships, Prizes, and Awards

- DC FemTech Awards (2019)
- ACM Distinguished Member (2018)
- ACM Distinguished Speaker (2017-2020)
- 2015 University of Maryland Research Communication Award
- 2014 University System of Maryland Board of Regents Mentoring Award
- TED Most Powerful Talks of 2014
- 2011 IEEE Conference on Social Computing Best Paper Award
- 2009 International Semantic Web Conference Best Paper Award
- Research Fellow, Web Science Research Initiative (2008 – present)
- IEEE Intelligent Systems Ten to Watch³ (May 2006)
- 2005 DARPA IPTO Young Investigator (May 2005)

2.K Editorships, Editorial Boards, and Reviewing Activities for Journals and Other Learned Publications

2.K.i Editorial Boards

- Editorial Board, IEEE Intelligent Systems (2017 - present)

³list of top ten young AI researchers

- Editorial Board, Data Science
- Editorial Committee, Journal of Web Semantics – Special Issue “Exploring New Interaction Designs Made Possible by the Semantic Web”
- Guest Editor, Security & Privacy Magazine, Special Issue on “Security in Social Networks”

2.K.ii Conference Chair Positions

- co-General Chair, **RecSys 2022**: Conference on Recommender Systems
- co-Workshops Chair, **RecSys 2021**: Conference on Recommender Systems
- Organizer, **Workshop on Online Harassment** at CHI2017
- Program co-chair, **RecSys 2015**: Conference on Recommender Systems
- Fellowships Chair, **ISWC 2012**: 11th International Semantic Web Conference
- Fellowships Chair, **ISWC 2011**: 10th International Semantic Web Conference
- Tutorials Co-chair, Program Committee Vice Chair, **ISWC 2009**: 8th International Semantic Web Conference
- Co-organizer, **SWUI 2009**: Semantic Web User Interactions: Exploring HCI Challenges Workshop at ISWC 2009.
- Co-organizer, Workshop on Social Technology for Biodiversity: Motivation, Credibility & Community, 2008
- Co-organizer, **SWUI 2008**: Semantic Web User Interactions: Exploring HCI Challenges Workshop at CHI’08
- Semantic Web Challenge Co-chair, **ISWC 2007**: 6th International Semantic Web Conference
- Semantic Web Challenge Co-chair, **ASWC 2007**: 2nd Asian Semantic Web Conference
- Co-organizer, Helping Users Make Sense of Social Networks: A Workshop, 2007
- Proceedings Chair, **ISWC 2006**: 5th International Semantic Web Conference
- Co-organizer, Workshop on Trust, Security, and Reputation on the Semantic Web, 2006
- Organizer, Developers Day Trust on the Web Track, **WWW 2005**: 13th International World Wide Web Conference

2.K.iii Reviewing: Journals

- ACM Transactions on Privacy: 2016(1)
- PLOS ONE: 2016 (1)
- ACM Transactions on Intelligent Systems: 2012 (2), 2016 (1)
- Foundations and Trends in Information Retrieval: 2015 (1)
- ACM Transactions on Computer-Human Interaction: 2014 (1)
- Foundations and Trends in Human Computer Interaction: 2013 (1)
- ACM Transactions on the Web: 2008 (2), 2009(1), 2012 (1), 2013 (1)
- Foundations and Trends in Web Science: 2012 (1)
- IEEE Security & Privacy: 2012(1)
- ACM Computing Surveys: 2012 (1)
- ACM Transactions on Internet Technology: 2009 (1)
- ACM Transactions on Multimedia Computing, Communications, and Applications: 2009 (1)
- Behaviour and Information Technology: 2008 (1)
- Artificial Intelligence: 2008 (1)
- European Journal of Operational Research: 2007 (1)
- Foundations and Trends in Information Retrieval: 2015 (1)
- Foundations and Trends in Web Science: 2013 (1),

- International Journal of Human Computer Studies: 2008 (1)
- International Journal on Semantic Web and Information Systems: 2007 (1)
- Journal of the American Society for Information Science and Technology: 2010 (1), 2011 (1), 2012 (1)
- Journal of Web Semantics: 2006 (1), 2007 (3), 2008 (1), 2012 (2)
- Policy & Internet: 2012 (1)

2.K.iv Reviewing: Top-Tier Conferences

- **DIS**: ACM Conference on Designing Interactive Systems, Reviewer 2017
- **RecSys**: ACM Conference on Recommender Systems, Senior Program Committee 2010-2018
- **WWW**: International World Wide Web Conference, Senior Program Committee, 2016-2018; Program Committee 2006-2015
- **CSCW**: Computer Supported Cooperative Work, Program Committee 2008, 201-2018
- **CHI**: ACM Conference on Human Factors in Computing, Reviewer / Program Committee 2009-2018
- **AAAI**: AAAI Conference on Artificial Intelligence, Senior Program Committee 2011, 2012, 2013; Program Committee 2006-2010
- **IJCAI**: International Joint Conference on Artificial Intelligence, Program Committee 2009
- **ISWC**: International Semantic Web Conference, Senior Program Committee 2009, 2010, 2011, 2012, Program Committee 2008
- **KDD**: Conference on Knowledge Discovery and Data Mining, Senior Program Committee 2010
- **GROUP**: Conference on Supporting Group Work, Program Committee 2009
- **IJCAI**: International Joint Conferences on Artificial Intelligence, Program Committee 2009

2.K.v Reviewing: Other Venues

- **SocInfo**: Social Informatics, 2016-2018
- **FATREC**: FATREC Workshop on Responsible Recommendation at RecSys 2017
- **ASONAM**: IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, 2013
- **PST**: Eleventh International Conference on Privacy, Security and Trust, 2013
- **IFIPTM**: International Conference on Trust Management, Program Committee 2009, 2010, 2011, 2012
- **IEA-AIE**: Engineering Knowledge and Semantic Systems, Program Committee 2011
- **SSW**: AAAI Symposium on the Social Semantic Web, Program Committee: 2009
- **WebSci**: Web Science Conference: Society On-Line International Semantic Web Conference, Program Committee 2008
- **BlogTalk**: International Conference on Social Software, Program Committee 2008
- **PST**: Conference on Privacy, Security and Trust, Program Committee 2008
- **SAC**: ACM Symposium on Applied Computing, Program Committee 2008, 2005
- **CoSoSo**: International Conference on Social Software, Program Committee 2008
- **IUI**: Intelligent User Interfaces Conference, Program Committee 2008
- **CEAS**: Conference on Email and Anti-Spam, Program Committee 2007
- **CIKM**: Conference on Information and Knowledge Management, Program Committee 2007
- **CAT**: Context Awareness and Trust, Program Committee 2007
- **Policy**: IEEE Policy, Program Committee 2007

- **SWC**: Semantic Web Challenge, Program Committee 2007
- **SCCSW**: Social and Collaborative Construction of Structured Knowledge Workshop, Program Committee 2007
- **SWCKA**: AAAI Fall Symposium on Semantic Web for Collaborative Knowledge Acquisition, Program Committee 2006
- **EKAW**: International Conference on Knowledge Engineering and Knowledge Management, Program Committee 2006
- **SECOVAL**: The Value of Security through Collaboration Workshop, Program Committee 2005, 2006.
- **SWUI**: Semantic Web User Interaction Workshop, Program Committee 2006
- **OWLED**: OWL Experiences and Directions, Program Committee 2006
- **SPTWS**: Workshop on Security, Privacy, and Trust in Web Services, Program Committee 2006
- **MTW**: Models of Trust Workshop, Program Committee 2006
- **OWLED**: OWL: Experiences and Directions Workshop, Program Committee 2005
- **FOAF**: Workshop on Friend of a Friend, Social Networking, and the Semantic Web, Program Committee 2004
- **SWUI**: First International Workshop on Interaction Design and the Semantic Web, Program Committee 2004
- **VIKE**: Visualizing Information in Knowledge Engineering (VIKE), Program Committee 2003

2.L Other

2.L.i External Talks (see section 2.E.i for keynote and similar talks)

- ‘Avoiding Dystopia’
MIT CSAIL HCI Seminar
Cambridge, MD (November 9, 2018)
- “Monster or Savior: Can Artificial Intelligence Go Rogue?”
AAAS Annual Meeting
Austin, TX (February 16, 2018)
- “Maximizing Value from Social Media”
Microsoft CEO Summit
Redmond, WA (May 17, 2017)
- “Algorithms That Find Your Secrets & Predict Your Future”
X-STEM Extreme STEM Symposium USA Science & Engineering Festival
Washington, DC (April 28, 2017)
- “The Curly Fry Conundrum”
Gore Creek Asset Management Family University
Key Largo, FL (April 7, 2017)
- “Foretold Futures from Digital Footprints: Artificial Intelligence, Behavior Prediction, and Privacy”
University of Pittsburgh Big Data Science Colloquium
Pittsburgh, PA (March 24, 2017)
- “Algorithmic Servants or Algorithmic Tyranny: Living With a Predicted Future”
University of Tennessee
Knoxville, TN (February 27, 2017)
- “Footprints in the Digital Dust: How Your Online Behavior Says More Than You Think”

- Washington & Lee University Mudd Center for Ethics
Lexington, VA (February 2, 2017)
- “Leveraging Social Data and Analytics”
Raytheon One Conference
Orlando, FL (November 3, 2016)
 - “The Business Power of Analytics”
Raytheon Senior Leadership Team Meeting
Sea Island, GA (October 28, 2016)
 - “The Human Side of Cybersecurity”
Salesforce Press Pause Speaker Series
San Francisco, CA (October 25, 2016)
 - “The Curly Fry Conundrum” and “Diamond Heists and Trust”
Nuclear Regulatory Commission HACK 2016 Conference
Rockville, MD (October 19, 2016)
 - “The Curly Fry Conundrum”
Microsoft Global CIO Summit
Redmond, WA (September 21, 2016)
 - “Big Social Data”
EnFuse 2016 - Guidance Software Annual Conference
Las Vegas, NV (May 25, 2016)
 - “The Power of Social Analytics”
Microsoft Global Accounts Summit
Washington, DC (April 27, 2016)
 - “Big Social Data”
Canadian Media Directors’ Council
Toronto, ON Canada (April 26, 2016)
 - “The Insights of Social Analytics”
HR People + Strategy Annual Conference
Scottsdale, AZ (April 12, 2016)
 - “Computing with Social Media”
Intel Science Talent Search
Washington, DC (October 17, 2015)
 - “Gaining Insights with Social Analytics”
Marketing Research Association Corporate Researchers Conference
St. Louis, MO (October 7, 2015)
 - “Big Social Data”
2015 American Nurses Credentialing Center Research Symposium
Atlanta, GA (October 6, 2015)
 - “Role of Social Media in Delivering High Quality Innovative Education”
Merck Professional Affairs Meeting
Chantilly, VA (October 1, 2015)
 - “Big Social Data”
Dairy Queen Supply Chain Summit
Cambridge, MD (September 23, 2015)
 - “The Curly Fry Conundrum”
Marketing Research Association Insights & Strategies Conference
San Diego, CA (June 4, 2015)
 - “Big Social Data”

- GS1's Connect 2015
Austin, TX (June 3, 2015)
- "Social Media Investigation"
Twin Cities Security Partnership
Minneapolis, MN (May 20, 2015)
 - "Computing with Social Data"
Coastal Carolina University Speaker Series
Myrtle Beach, SC (April 28, 2015)
 - "Insights from Big Social Data"
Association of Executive Search Consultants Global Conference
New York, NY (April 15, 2015)
 - "The Curly Fry Conundrum"
WBL Foundation Summit
Dallas, TX (March 18, 2015)
 - "Predicting User Attributes in Social Media"
Society 2013
State College, PA (May 9, 2013)
 - "Generational Computing and Social Media"
Department of Defense Deep Dive on Obesity
Portsmouth, VA (August 19, 2012)
 - "Information Sharing in Social Networks"
FBI Lookout Group Meeting
Dallas, TX (August 14, 2012)
 - "Social Networks and HCI Research"
National Reconnaissance Office
Chantilly, VA (March 15, 2012)
 - "Information Sharing in Social Networks"
Potomac Valley Chapter (PVC) of the American Society of Information Science and Technology
Washington, DC (April 10, 2012)
 - "Computing Trust and Personality in Social Networks"
Aberdeen Proving Ground Network Science Meeting
Aberdeen, MD (March 5, 2012)
 - "Managing Content With Trust"
Professional & Scholarly Publishers 2012 Annual Conference
Washington, DC (February 2, 2012)
 - "Information Sharing in Social Networks"
FBI Lookout Group Meeting
Dallas, TX (January 9, 2012)
 - "From Open Data to Open Worlds: The Power of the Semantic Web" World Bank Information Management Technology Group Forum
Washington, DC (December 8, 2011)
 - "Information Sharing in Social Networks"
FBI Headquarters – Counterintelligence Division All-hands Meeting
Washington, DC (November 17, 2011)
 - "Predicting Personality from Social Media"
FBI Counterintelligence Behavioral Analysis Unit
Quantico, VA (November 1, 2011)

- “Computing with Social Trust”
Army Research Lab Seminar Series
Adelphi, MD (December 8, 2010)
- “Computing with Social Trust”
Aberdeen Proving Ground CTA Seminar
Aberdeen, MD (November 16, 2010)
- “Personality Traits and Facebook Profiles”
Social and Cognitive Network Academic Research Center Seminar Series
Rensselaer Polytechnic Institute, Troy, NY (April 18, 2010)
- “Social Recommender Systems on the Semantic Web”
National Archives Semantic Web Myth and Fact
Washington, DC (November 17, 2009)
- “Social Software in Digital Libraries and Archives”
Online Computer Library Center (OCLC)
Arlington, VA (November 5, 2009)
- “Tutorial on Using Social Trust for Recommender Systems”
ACM Conference on Recommender Systems (RecSys ’09)
New York, New York (October 22, 2009)
- “Recommender Systems, Social Trust, and Television Applications”
StreamSage (a division of Comcast)
Washington, DC (September 9, 2009)
- “Social Networks on the Semantic Web”
Microsoft Research Faculty Summit
Redmond, Washington (July 28, 2008)
- “Understanding Social Networks”
The 25th Annual Human-Computer Interaction Lab Symposium
College Park, Maryland (May 29, 2008)
- “Social Networks and Intelligent Systems: Using Relationships for Information Access”
University of Illinois Urbana-Champaign HCI Seminar
Urbana, Illinois (February 29, 2008)
- “Social Networks and the Semantic Web”
Invited talk at Rensselaer Polytechnic Institute
Troy, New York (February 4, 2008)
- “Recommending Movies with Social Networks”
StreamSage / Comcast
Washington, DC (November 2007)
- “Social Information Access: Connecting Distributed Information and People on the Web”
Presentations with similar titles and content given in the following venues
 - Northeastern University College of Computer and Information Science
Boston, Massachusetts (February 2007)
 - University of Maryland College of Information Studies
College Park, Maryland (February 2007)
 - Drexel College of Information Science and Technology
Philadelphia, Pennsylvania (April 2007)
- “Analysis and Applications of Web-based Social Networks”
University of Illinois at Urbana-Champaign Age of Networks: Social, Cultural, and Technological Connections Speaker Series

- Urbana, Illinois (January 22 2007)
- “Provenance Challenge: A Semantic Web Approach”
Global Grid Forum – GGF18/GridWorld
Washington, DC (September 13 2006)
 - “The Other Kind of Networking: Social Networks on the Web”
Duke University (March 2006)
 - “Web-based Social Network Analysis for Socially Intelligent Applications”
University of Illinois at Chicago (November 2005)
 - “Trust in Social Networks”
National Security Agency’s Knowledge Discovery Research Colloquium
Ft. Meade, Maryland (August 2005)
 - “Connections, Computation, and Cinema”
Presentations with similar titles and content given in the following venues
 - University of Georgia, March 2005.
 - MIT Media Lab, March 2005.
 - “Inferring Trust in Web-based Social Networks”
National Security Agency
Ft. Meade, Maryland (February 2005)
 - “Trust on the Semantic Web”
Thirteenth Annual World Wide Web Conference Developers Day
New York, New York (May 2004)
 - “The Semantic Web as a Complex System”
International Conference on Complex Systems
Boston, Massachusetts (May 2004)
 - “Metadata Visualization Challenges”
NASA Goddard Semantic Web Interest Group
Greenbelt, Maryland (November 2003)
 - “Semantic Web: Structure and Modeling”
Half-day workshop at the Howard University
Washington, DC (June 2003)
 - “Putting Time into Cognitive Systems: From Real-Time Operating Systems to Information Dynamics”
Virtual Worlds and Simulation Conference
Orlando, Florida (January 2003)
 - “Tools on the Semantic Web”
Half-day workshop at the Howard University
Washington, DC (November 2002)
 - “Small Worlds on the Semantic Web”
Science on the Semantic Web (SWS) Workshop
Boston, Massachusetts (October 2002)
 - “Evolving Strategies for the Prisoner’s Dilemma”
13th International Conference on Game Theory
Stony Brook, New York (July 2002)
 - “Semantic Web Do-It-Yourself: Tools for Generating RDF Content”
NASA Goddard Semantic Web Interest Group
Greenbelt, Maryland (April 2002)

2.L.ii Internal Talks

- “Big Social Data”
3rd Annual Administrative Professionals Conference
College Park, MD (July 27, 2018)
- “Big Social Data”
Big 10 Counseling Conference
College Park, MD (February 23, 2018)
- “The Curly Fry Conundrum”
Counseling Center’s Research and Development Series
College Park, MD (March 29, 2017)
- “The Power of Big Social Data”
Engineering and Physical Sciences Library STEAM Salon
College Park, Maryland (March 15, 2017)
- “The Curly Fry Conundrum”
Fearless Ideas Series
College Park Maryland (August 30, 2015)
- “Video Chat for Pets”
HCIL Symposium
College Park, Maryland (May 22, 2012)
- “Social Network Strategies for Surviving the Zombie Apocalypse”
HCIL Symposium
College Park, Maryland (May 22, 2012)
- “The Twitter Mute Button”
HCIL Symposium
College Park, Maryland (May 22, 2012)
- “Understanding Users and Relationships in Social Networks”
MURI Virtual Brown Bag
College Park, Maryland (April 9, 2012)
- “Computing Trust in Social Networks”
Guest Lecture to PSY228Q: The psychology of social networking and social computing
College Park, Maryland (April 2, 2012)
- “Social Computing 2”
Guest Lecture to CMSC434: Intro to HCI
College Park, Maryland (November 30, 2011)
- “Social Computing 1”
Guest Lecture to CMSC434: Intro to HCI
College Park, Maryland (September 21, 2011)
- “Understanding Users and Relationships in Social Networks”
HCIL Symposium
College Park, Maryland (May 25, 2011)
- “Trust, Ties, and Information Diffusion in Social Networks”
Guest Lecture in INFM289j: Social Media Campaigns for the WellBeing of Humankind
College Park, Maryland (November 22, 2010)
- “Recommender Systems, Social Networks, and Applications”
Guest lecture to CPSP218J: Media, Self, and Society
College Park, Maryland (September 20, 2010)
- “Twitter Use by the US Congress”

HCIL Symposium

College Park, Maryland (May 26, 2010)

- “Recommender Systems, Social Networks, and Applications”
Guest lecture to CPSP218J: Media, Self, and Society
College Park, Maryland (September 8, 2009)
- “Designing Systems to Help Find Experts”
iSchool Colloquium
College Park, Maryland (September 15, 2008)
- “Social Networks on the Web: Challenges and Opportunities”
Smith School of Business, University of Maryland
College Park, Maryland (March 14, 2008)
- “Social Trust for Information Access”
Center for Information Policy and E-Government (CIPEG) Policy Seminar Series
College Park, Maryland (February 25, 2008)
- “Social information access -using social networks to sort, filter, and aggregate”
Human-Computer Interaction Lab (HCIL) Brown Bag Lunch
College Park, Maryland (November 8, 2008)
- “Inferring Trust in Social Networks for Information Presentation”
Computational Linguistics and Information Processing (CLIP) Lab Colloquium
College Park, Maryland (October 3, 2007)

2.L.iii Panels⁴

- Panelist, “Reflecting on Hybrid Events: Learning from a Year of Hybrid Experiences”, CHI 2023, Hamburg, Germany
- Panelist, “Will Artificial Intelligence be a net benefit to scientific research?”, Artificial Intelligence Citizen’s Assembly, April 25, 2023, University of Birmingham, UK
- Moderator “Fighting Disinformation to Save Democracy”, iSchool Alumnia Event, March 3, 2019, Bethesda, MD
- Panelist, “Online nonsense: tools and teaching to combat fake news on the Web”, iConference 2019, College Park, MD
- Panelist, “The Lines Between Censorship and Responsibility”, Global Policy Institute, March 27, 2019, Washington DC
- Panelist, “The 2016 US Presidential Election and HCI: Towards a Research Agenda”, CHI 2017, May 11, 2017, Denver, CO
- Moderator, “Get Engaged, Get Involved–Mobilizing Involvement through Technology and Setting the Stage for Future Generations”, Belmont-Paul Womens Equality National Monument Women’s History Month (March 21, 2017)
- Panelist, “Cozy with Cookies: our Brain and Behavioral Targeting”, South by Southwest (SXSW), March 11, 2017, Austin, TX
- Panelist, Department of Homeland Security 2017 Big Data Series - Learning from Social Media Challenges and Opportunities, March 3, 2017
- Panelist, “Creating the Future of Data Science: New Horizons for Education and Training”, White House Federal Data In Action Summit, December 15, 2016, Washington DC
- Panelist “The Campaign and your Brain”, Caltech Association October 27, 2016 Washington, DC

⁴ Appearances on panels, not accompanied by papers. Refereed or invited as noted.

- Moderator, “Weapons of Math Destruction: Author Discussion”, Politics & Prose, September 20, 2016, Washington DC
- Panelist, “Me and My Matrix? The Future of Humans and Computers”, Sci Fi Museum Con, July 1, 2016, Alexandria, VA
- Panelist, “Media and the Courts”, New Mexico Judicial Conclave, June 17, 2016 Albuquerque, NM
- Panelist, “Is Big Brother Alive and Well?”, Virginia Military Institute 2016 Leadership Conference, March 6, 2016 Lexington, VA
- Panelist, “#distractinglySexy: Using Twitter to Fight Sexism in Science Online“, South by Southwest (SXSW), March 14, 2016, Austin, TX
- Panelist, “Is Big Brother Alive and Well?”, Virginia Military Institute Cyber Ethics Conference, March 7, 2016, Lexington, VA
- Panelist, “Are you in a social media experiment?”, South by Southwest (SXSW), March 14, 2015, Austin, TX
- Panelist, “Opportunities and Risks of Discovering Personality Traits from Social Media”, Toronto, Canada
- Panelist, Social Media, NewsVision (digital media conference), March 30, 2009, Washington, DC
- Panelist, Data Fusion and Data Enrichment Panel, Director of National Intelligence Open Source Conference, July 2007, Washington, DC

2.M Op-eds

- Wired: Theres No Excuse to Ignore Warnings of Domestic Terrorism (January 12, 2021)

2.M.i Media Mentions

Online and Print Media - Major Publications

- CNN: Pentagon leak spotlights surprising interplay between gaming and military secrets (April 22, 2023)
- WTOP: It may sound like a family member on the phone but it could be a scammer (March 6, 2023)
- Worcester Telegram: How companies and social media use algorithms to make ‘scary’ predictions about you (March 10, 2022)
- WUSA9: Apple, Google team up for contact tracing tech to help fight coronavirus (April 17, 2020)
- SyFy: The Stranger Quibi Source: Quibi Quibi’s The Stranger: How creator Veena Sud made a tech horror series for your phone (April 14, 2020)
- NBC4: TSA Employees Vent About Management, Passengers on Private Facebook Page (October 28, 2019)
- Fortune: Twitter, Unable to Control Its Worst Elements, Rolls out a Site Redesign (Jul 16, 2019)
- NBC News: Mason jars and drama: How an Instagram influencer’s event tour captivated the internet (January 2019)
- CNBC: Fans are using Venmo to tip celebrities like Bears QB Mitchell Trubisky and SNL’s Michael Che (January 2019)
- Minnesota Public Radio News: Inside the world of an internet troll: How web users can protect themselves online (Apr 24, 2019)

- Fortune: Twitter and Instagram Are Starting to Imagine a World Without Likes (May 1, 2019)
- New York Post: Is this viral cooking hack the best way to peel garlic? (Jun 17, 2019)
- NBC4 Washington: TSA Employees Vent About Management, Passengers on Private Facebook Page (Oct 28, 2019)
- Gizmodo UK: Starlink Satellites Produce Wave of UFO Sightings in the US (Dec 28, 2019)
- NBC News: 19 bold predictions for science and technology in 2019 (December 27, 2018)
- Scientific American: The Facebook Controversy: Privacy Is Not the Issue (April 18, 2018)
- NBC News: About 600 questions later, Zuckerberg and Congress leave major issues about Facebook unanswered (April 12, 2018)
- NBC News: Tech companies struggle with the human side of fake news (March 17, 2018)
- NBC News: Twitter CEO asks for help in fixing its toxic environment (March 1, 2018)
- Huffington Post: The Teens Are Coming For The NRA, And They Can't Be Stopped (February 25, 2018)
- NBC News: How Parkland's social media-savvy teens took back the internet (February 22, 2018)
- Wired: People Can Put Your Face on Porn and the Law Can't Help You (January 26, 2018)
- Newsweek: Melania Trump Is Very Concerned About Appearance, Rarely Shows Flaws, Unlike Previous First Ladies (January 3, 2018)
- Washington Post: Seen but rarely heard: How Melania Trump is approaching the public role of first lady. (January 2, 2018)
- NBC News: Facebook at a crossroads as it rides huge profits, battles backlash (November 17, 2017)
- Baltimore Sun: House committee releases Russian-linked ad depicting Freddie Gray (November 1, 2017)
- NBC News: Why Did Twitter Suspend Rose McGowan? (October 12, 2017)
- NBC News: Social Media Becomes a Savior in Hurricane Harvey Relief (August 28, 2017)
- Christian Science Monitor: Fallout from modern protests: naming and shaming online (August 17, 2017)
- Wired: Twitter's Meme War Isn't About Civility, It's About Money (June 29, 2017)
- Prevention: 7 Appropriate Ways To Handle Grief On Facebook When You Lose A Loved One (June 1, 2017)
- NBC News: Whose Responsibility Is It to Police Content on Facebook? (May 9, 2017)
- Wired: Facebook's New Plan May Curb Revenge Porn, But Won't Kill It (April 6, 2017)
- Wired: Silly YouTube, Don't You Know Making the Internet Nicer Is Impossible? (March 22, 2017)
- NBC News: Who's Policing Facebook's Secret Groups? (March 7, 2017)
- Christian Science Monitor: AP-NORC poll: Teens cynical about politics, yet many remain hopeful (February 28, 2017)
- NBC News: What Could Happen if President Trump's Twitter Gets Hacked? (February 22, 2017)
- Deutsche Welle: 'I literally wake up in the middle of the night' (February 14, 2017)
- Deutsche Welle: Scientists in the US band together against Donald Trump (February 13, 2017)
- Libération: Donald Trump : Les ttes chercheuses rpliquent (February 12, 2017)
- ABC News: Medical and Science Communities Could Take a Blow From Trump's Immigration Order (January 30, 2017)
- New York Times: Science Will Suffer Under Trump's Travel Ban, Researchers Say (January

- 30, 2017)
- Chronicle of Higher Education: Shock, Despair, and Outrage: Academics Condemn Trumps Immigration Crackdown (January 30, 2017)
 - The Atlantic: Trumps Immigration Ban Is Already Harming American Science (January 29, 2017)
 - BuzzFeed: The Online Revolt Of National Parks Has Created A Political Movement (January 27, 2017)
 - Deutsche Welle: Scientists fight back against Trump (January 27, 2017)
 - NBC News: Where Do We Draw the Line When It Comes to Free Speech Online? (December 7, 2016)
 - NBC News: What Would It Take to Shut Down Trump on Twitter? (December 6, 2016)
 - The Telegraph: 'Frustrated' computer scientist gives perfect response to 'patronising' tweet (October 5, 2016)
 - Huffington Post Canada: This Mansplaining Tweet Shows Why It's Frustrating To Be A Woman In Tech (October 7, 2016)
 - Huffington Post: Computer Science Professor Shuts Down Mansplainer Like A Boss (October 5, 2016)
 - PolitiFact: Trump says Twitter, Google, Facebook buried Clinton emails story (November 2, 2016)
 - New Scientist: What your social media profile photo says about your personality (May 20, 2016)
 - USA Today: Why do people sound off on Twitter? Kim Kardashian's Twitter rant explained (March 8, 2016)
 - Gizmodo: This Sinister Software Tells You How to Craft the Perfect Email (September 28, 2015)
 - Huffington Post: Why Dogs Just Cant Seem To Recognize Us On Our Phones And Tablets (June 2, 2015)
 - New York Times: Dressing for TED: What to Wear to Go Viral (March 11, 2015)
 - Computerworld: Computers may soon know you better than your spouse (January 13, 2015)
 - Fortune Magazine: CONTAGION – From Justin Bieber to data scientists, how Twitter got hot in the academy (August 22, 2014)
 - Huffington Post: The Fall of Facebook - and What's Next (June 25, 2014)
 - Associated Press: What you 'like' on Facebook can be revealing (March 11, 2013)
 - Politico: 'Weinergate' a cautionary tale? (May 31, 2011)
 - Daily Caller: Facebook can serve as personality test (May 23, 2011)
 - ABC News: Facebook can serve as personality test (May 13, 2011)
 - Jezebel: Your Facebook Is The New "Personality Test" (May 13, 2011)
 - Time: Put Your Best Face Forward: Facebook Deemed an Accurate Personality Test for Employers (May 10, 2011)
 - ABC Online: Facebook can serve as personality test (May 9, 2011)
 - Discovery News: Facebook can serve as personality test (May 9, 2011)
 - New Scientist: Why Facebook friends are worth keeping (July 15, 2010)
 - Baltimore Sun: Congressional Twitter mostly twaddle (September 21, 2009)
 - Huffington Post: Politicians On Twitter: Tweets By Lawmakers Boastful Or Boring: Study (September 19, 2009)
 - The Hill: Lawmakers' Tweets Largely Self-Promotional (September 18, 2009)
 - The Washington Post: Politicians' Tweets Are Mostly Self-Promotional, Researchers Say (September 18, 2009)

- Politico: Study: Congress Needs Twitter Help (September 16, 2009)
- Ars Technica: Who do you trust 2.0: Building better preference predictions (September 21, 2008)
- Wired.com: Obama Supporters Act to Clear FUD. (November 12, 2007)
- Salon.com: You are who you know (June 15, 2004)

Online and Print Media - Other Outlets

- The Wire: Inside the Minds of Internet Trolls: A Psychological Analysis (April 27, 2020)
- PYMTS: New York Security Law Changes Retail Data Efforts (Feb 27, 2020)
- Book Riot: Why Do People Choose To Publish Their Books Via Kickstarter? (Feb 7, 2020)
- KXLH Helena News: Strange lights seen in the sky in northern Montana are likely SpaceX 'Starlink' satellites (Dec 26, 2019)
- Redheaded Blackbelt: Strange Line of Lights in the Sky Was Reported by Multiple Readers (Dec 24, 2019)
- Dual Dove: Train of UFOs in the Sky Were, in Fact, the Starlink Satellite Constellation (Dec 30, 2019)
- Mic: Oversharing online: The power and danger of saying too much (Aug 23, 2019)
- WLKY Louisville: Belski's Blog - See the Starlink satellites tonight (Dec 23)
- Fortune: Twitter Hopes Users Will Love Its Redesigned Desktop Layout And Replace All the Bots Its Been Purging (January 2019)
- Russian Machine Never Breaks: Christian Djoos needed surgery for compartment syndrome in his left thigh (January 2019)
- MarketWatch: One year after Zuckerbergs testimony about violent content on Facebook, has anything changed? (March 20, 2019)
- The Cheat Sheet: Kyle Richards from 'RHOBH' Reminds Fans That None of the Cast Members Are Horrible People (March 5, 2019)
- Inquirer: Online customer agents can see what youre typing even before you hit that send button (November 30, 2018)
- The Jewish Voice: Facebook Grappling With The Role it Plays in Suicides (July 14, 2018)
- MarketWatch: She posted a photo on Facebook moments before taking her own life it took her family days to remove it (July 18, 2018)
- Fox 5 NY: Why toxicity thrives on Twitter (June 1, 2018)
- KUOW: Think data privacy is dead? Try replacing the word 'privacy' with 'consent' (April 16, 2018)
- New York Daily News: Facebook users shouldnt be surprised by how closely their data is being tracked (March 23, 2018)
- KUOW: Talking Facebook (and My Dinner with Andre) on KUOW (March 22, 2018)
- MIT Technology Review: Twitter wants to reduce the health of its conversations to four numbers. Good luck, say experts. (March 8, 2018)
- MN News Today: Keeping Your Children Safe Online (January 11, 2018)
- The Lily: How Melania Trump is approaching the public role of first lady (January 5, 2018)
- Stars and Stripes: How Melania Trump is approaching the public role of first lady (January 2, 2018)
- CustomerThink: In the Digital Revolution, Customers Have Nothing to Lose But Their Privacy (July 31, 2017)
- The SandPaper: Rotting Takes a Turn for the Better; Trolls Give Trolling a Bad Name (May 10, 2017)

- Temple City Tribune: Why Employers Want Millennials With Social Media Skills (May 10, 2017)
- WDEF, Facebook, for the first time, acknowledges election manipulation (April 29, 2017)
- San Diego Union-Tribune: Anyone can discover your secrets from your public social media data (April 22, 2017)
- WJLA: University of Maryland students to attend March for Science in DC (April 21, 2017)
- KVOA” Cleveland Shooting Highlights Facebooks Responsibility in Policing Depraved Videos (April 17, 2017)
- Nanalyze: 7 Startups Giving Artificial Intelligence (AI) Emotions (April 10, 2017)
- Charleston Gazette-Mail: On Retirement: Periods are passe, among other lessons learned from texting (March 28, 2017)
- Marketwatch: Being under surveillance changes our behavior (and not for the better) (March 6, 2017)
- Merdeka: Apa jadinya kalau akun Twitter Presiden Trump dibajak? (February 22, 2017)
- The Diamondback: One UMD professor asked foreigners to help U.S. scientists stuck abroad. 1,000 answered. (February 5, 2017)
- FranceInter: Les scientifiques aussi se mobilisent contre le decret anti-immigration de Trump (February 2, 2017)
- Inverse.com: Trump’s Iran Travel Ban Gutpunched American Science (January 31, 2017)
- Frankfurter Allgemeine Zeitung: Akademiker gegen Trump: Alarm im Wissenschaftsmekka (January 30, 2017)
- Newsmax: Academics Worry Trump’s Ban Impacts Education, Science (January 30, 2017)
- Inverse: Trump’s Iran Travel Ban Gutpunched American Science (January 30, 2017)
- Milli Gazette: Trolling Syndrome Not Just a Namesake (December 31, 2016)
- Amanha: Notcias falsas nas mdias sociais: qual a soluo? (December 12, 2016)
- World Politics Review: What Should Tech Giants Do About Hate Speech on Their Platforms? (December 9, 2016)
- Value Walk: How Could Trump Be Shut Down On Twitter? (December 9, 2016)
- Kojo Nnamdi Show Blog: Park Views Colony Club May Symbolize Gentrification, But Its Owner Hopes Its The Positive Kind (December 6, 2016)
- Christian Science Monitor: Many teens have trouble spotting fake news, but it’s not as bad as it sounds (November 22, 2016)
- Knowledge@Wharton (Sirius/XM Business Radio blog): Fake News, Hate Speech and Social Media Abuse: Whats the Solution? (November 21, 2016)
- Urgente 24: Facebook & PayPal: Los bancos estn temblando (November 11, 2016)
- Slidebot Blog: 5 Presentations That Explain How Social Media Works (November 7, 2016)
- Grinding my Grits Blog: Internet Trolls: A Repost (November 5, 2016)
- Knowledge@Wharton (Sirius/XM Business Radio blog), Knowledge@Wharton (Sirius/XM blog): Will Twitter Find Its True Calling? (November 4, 2016)
- Safe Routes Partnership Blog: Pokmon Go and the Gamification of Active Travel (November 4, 2016)
- Scary Mommy: Mansplaining Was Featured On Jeopardy! And It Was Perfect (October 31, 2016)
- Knowledge@Wharton (Sirius/XM Business Radio blog): The Facebook-PayPal Partnership: Who Benefits Most? (October 26, 2016)
- Huffington Post Korea: ‘ ‘ ? (October 7, 2016)
- More: The Most Face-Palm Examples Of Mansplaining On The Internet (October 7, 2016)
- Mashable avec France 24: Sexisme ordinaire : une prof d’informatique rabat le clapet d’un

- internaute qui a parl trop vite (October 6, 2016)
- Bento: Wie sich eine Professorin gegen Sexismus zur Wehr setzt (October 5, 2016)
 - Mashable: Computer scientist shuts down mansplainer who told her to learn Java (October 5, 2015)
 - edul Virginia Foundation for the Humanities: Can Curly Fries Predict the Future? (September 5, 2016)
 - America Economia: Un emoji vale ms que mil palabras? (August 5, 2016)
 - Netkwesties: AH leert jongeren etiquette met Pokemon Go (July 22, 2016)
 - Knowledge@Wharton (Sirius/XM Business Radio blog): Say It With a Smile: Is an Emoji Worth a Thousand Words? (July 18, 2016)
 - Illinois Public Media: Look At You Now, A Memoir; Millennium Park Protest; Pokmon Go Goes To College (And Everywhere) (July 12, 2016)
 - Sciencenet.cn: (May 31, 2016)
 - Quartz: Digital spring-cleaning tips to help speed up and secure your devices (May 27, 2016)
 - LIFO: : : (May 3, 2016)
 - KUOW (Seattle Public Radio): Not So Far-Fetched: How Cats And Dogs Can Use Gadgets You Already Own (April 22, 2016)
 - Stuff: Why do people rant on Twitter? (March 20, 2016)
 - Eagle Strategies Blog: Jennifer Golbeck for TEDx: What Companies and SNS know about you (March 6, 2016)
 - Washington Independent Review of Books: Bedtime Stories: February 2016 (February 26, 2016)
 - Diane Rehm Show Blog: Your Questions Answered: Anonymous Messaging App Safety (February 21, 2016)
 - Business.com: Crystal Knows All: Youre Being Profiled (January 14, 2016)
 - Healthcare IT News: Is health data privacy even possible in the social media age? (November 4, 2015)
 - Las Vegas Review Journal: The real reason Facebook added six emojis and not a 'Dislike' button (October 12, 2015)
 - MIT Technology Review: How Benford's Law Reveals Suspicious Activity on Twitter (April 21, 2015)
 - Ideas.ted.com: What are you revealing online? Much more than you think (July 1, 2014)
 - Library of Congress Blog: Understanding User Generated Tags for Digital Collections: An Interview with Jennifer Golbeck* (May 1, 2013)
 - Seattle Post Intelligencer: What Facebook tells your boss about your personality (May 9, 2011)
 - Hindustan Times: Facebook's employee personality test (May 10, 2011)
 - Corp Comms Magazine: Politicians Tweet Sweet Nothings (September 22, 2009)
 - Sacramento Bee: Tweet-tweet goes Schwarzenegger, a big Twitter user (September 22, 2009)
 - Stars & Stripes (U.S. Military Newspaper)
 - Japan Edition (September 22, 2009)
 - Mideast Edition (September 22, 2009)
 - Korea Edition (September 21, 2009)
 - USTINET News: Study: Congress Tweets Lack Citizen Talk (September 21, 2009)
 - United Press International: Study: Congress Tweets lack citizen talk (September 21, 2009)
 - San Diego Union-Tribune: Politicians on Twitter have a lot to say about themselves (September 20, 2009)

- Lawrence Journal World & News: Members of Congress tweet their own horns (September 20, 2009)
- The Telegraph (Calcutta, India): Blowing tweet horns (September 20, 2009)
- The News Journal (Wilmington, DE): For Twitter-happy politicians, the service is all about them (September 20, 2009)
- Honolulu Advertiser: Politicians' Tweets self-promotional (September 20, 2009)
- Hawaii Reporter: Politicians' Tweets Are Mostly Self-Promotional, Researchers Say (September 19, 2009)
- Austin American Statesman: Lawmakers use Twitter for self-promotion, study finds (September 19, 2009)
- The Arizona Republic: Surprise! Twitter from D.C. about self-promotion (September 18, 2009)
- St. Petersburg Times: Times Wires (September 18, 2009)
- Kansas City Star: Study: Congress all a Twitter (September 15, 2009)
- Delmarva Daily Times: ALL ABOUT ME: '25 Things' becomes one of Facebook's biggest fads. (February 27, 2008)
- WEYI NBC25: Facebook backs down on change (February 18, 2009)
- Physics World: Talking Physics in the Social Web (January 2007)

Podcasts, Radio, and TV - Hosting

- SCIENCE Magazine, host of podcast books segment (January 2017 - present)
- NPR, The Kojo Nnamdi Show, guest host⁵ (2014-2019)

Podcasts, Radio, and TV - Guest

- MSNBC 11th Hour, January 8, 2021; January 13, 2021; January 21, 2021; March 3, 2021; November 22, 2021
- Sirius/XM Business Radio, Knowledge@Wharton regular guest on tech issues, 2016 - 2019
- NPR News, "Upworthy Was One Of The Hottest Sites Ever. You Won't Believe What Happened Next" (June 20, 2017)
- NPR, The Diane Rehm Show, (June 9, 2017, November 23, 2016; February 16, 2016; January 8, 2016; July 10, 2006)
- WJLA, University of Maryland students to attend March for Science in DC (April 21, 2017)
- Here & Now (NPR), interview on getting off social media (March 31, 2017)
- MSNBC, Pulse of America, interview on fake news (December 11, 2016)
- NPR, To The Point, interview on social media (January 3, 2014)
- NPR, The Kojo Nnamdi Show, March 21, 2013; July 31, 2012; June 12, 2012; February 28, 2012; October 31, 2011; March 24, 2011; February 15, 2011
- Wisconsin Public Radio, The Joy Cardin Show, interview on "What your Facebook Likes say about you" (March 21, 2013)
- NPR, interview on social media and the Olympics (August 1, 2012)
- NPR, The Animal House, interview on social networks for pets (January 15, 2011)
- BBC World Service Newshour, interview on Twitter use by PMs (October 21, 2009)
- WHIO TV, interview on the use of Twitter by Congress (October 3, 2009)
- KCSN Radio, interview on the use of Twitter by Congress (September 21, 2009)
- WTOP Radio, interview on the use of Twitter by Congress (September 15, 2009)

⁵I fill in when the host is out, usually 1-2 hours per month

- NBC 4, TV interview on Facebook data sharing policy (February 17, 2009)
- Science Podcast, interview on trust in social networks (September 18, 2008)
- NBC 4, TV interview on internet predators (February 21, 2008)

3 Teaching, Mentoring, and Advising

3.A Courses Taught in the Last Five Years

Enrollment numbers are given parenthetically by each section

- INST 627: Data Analytics for Information Professionals
 - Fall 2019(enrollment 30)
- INST326: Object Oriented Programming
 - Spring 2020 (48)
 - Spring 2019 (55)
- INST141: Data Science Techniques
 - Fall 2018 (51)
- ENMP 809G: Network Data Science
 - Spring 2018 (30)
- INST808: Social Network Analysis
 - Fall 2022 (12)
- INST151 / INST408N / INST608N: Becoming a Social Media Influencer
 - Fall 2022 (98)
 - Summer 2022 (12)
 - Summer 2021 (28)
 - Summer 2020 (46)
- INST155 / INFM 289i: Social Networks: Technology and Society
 - Fall 2021 (135)
 - Spring 2021 (135)
 - Fall 2020 (125)
 - Spring 2020 (136)
 - Fall 2019 (100)
 - Spring 2019 (80)
 - Fall 2018 (80)
- INST 462: Information Visualization
 - Fall 2018 (45)
 - Spring 2019 (93)
 - Summer 2019 (44)
 - Fall 2019 (93)
 - Spring 2020 (39)
 - Summer 2020 (46)
 - Fall 2020 (96)
 - Winter 2021 (29)

- Spring 2021 (88)
 - Winter 2022 (32)
 - Summer 2022 (27)
- INST 631 / LBSC795: Fundamentals of HCI
 - Fall 2018 (enrollment 40)
- INST 632 Human Computer Interaction Design Methods
 - Spring 2018 (enrollment 25)
- INST 633 / LBSC708L: Analyzing Social Networks and Social Media
 - Summer 2022 (enrollment 8)
 - Winter 2022 (enrollment 27)
 - Summer 2021 (enrollment 8)
 - Winter 2021 (enrollment 16)
 - Summer 2020 (enrollment 23)
 - Winter 2020 (enrollment 24)
 - Summer 2019 (enrollment 14)
 - Winter 2019 (enrollment 20)
 - Summer 2018 (enrollment 13)
 - Winter 2018 (enrollment 24)
- INST670 / INST728N: Intro to Javascript
 - Summer 2022 (enrollment 8)
 - Winter 2022 (enrollment 8)
 - Summer 2021 (enrollment 8)
 - Winter 2021 (enrollment 8)
 - Summer 2020 (enrollment 8)
 - Winter 2020 (enrollment 8)
 - Summer 2019 (enrollment 8)
 - Winter 2019 (enrollment 8)
 - Summer 2018 (enrollment 9)
 - Winter 2018 (enrollment 8)
- INST673: Hands on Machine Learning with Weka
 - Winter 2022 (enrollment 6)
 - Winter 2021 (enrollment 10)
 - Winter 2020 (enrollment 16)
 - Winter 2019 (enrollment 17)
- INST671 / INST728W: Intro to Web Programming
 - Winter 2022 (enrollment 10)
 - Winter 2021 (enrollment 9)
 - Winter 2020 (enrollment 15)
 - Winter 2019 (enrollment 20)
 - Winter 2018 (enrollment 7)
 - Winter 2017 (enrollment 12)
 - Winter 2016 (enrollment 11)

3.B Course or Curriculum Development

- Fall 2018: Developed online version of INST 462: Information Visualization
- Spring 2017: Developed online version of INST 627, new prep / redevelopment of INST632
- Fall 2015: Developed 1-credit classes on HTML and Javascript to be offered regularly online
- Fall 2012: Development of HCI Masters capstone classes, INST 775 and 776
- Fall 2011: Redevelopment of LBSC795 / INST631 for HCI Masters program
- Spring 2010: First offering of new course for undergraduate iSeries, INFM289I: Social Networks, Technology, and Society
- Winter 2010. Developed online version of LBSC690: Information Technology
- Spring 2009. First offering of new course. INFM 743: Development of Internet Applications
- Spring 2009. Significant course revision. LBSC 690: Information Technology
- Spring 2008. First offering of new course. INFM 220: Information Users in Social Context
- Fall 2007. Development of new course LBSC 888: Doctoral Seminar (with Allison Druin)
- Spring 2007. First offering of new course. CMSC 498N: Small Worlds, Social Networks, and Web Algorithms

3.C Textbooks, Manuals, Notes, Software, Web pages and Other Contributions to Teaching

3.C.i Textbooks

- **Jennifer Golbeck**, Analyzing the Social Web Burlington, MA: Morgan Kaufmann, 2013.

3.E Advising: Other Than Research Direction

3.E.i Undergraduate

- Anthony Rogers, Individual Studies Program, Fall 2007 – Spring 2015
- Ben Falk, Individual Studies Program, Spring 2008 – Spring 2012
- Ryan McCormick, Individual Studies Program, Spring 2008 – Spring 2011

3.E.ii Master's

- Spring 2009: 13 advisees
- Fall 2008: 13 advisees

3.F Advising: Research Direction

3.F.i Undergraduate

- Danny Laurence
Spring 2012
Research topic: Computing trust in social networks
- Elaine Wang
Spring 2012
Research topic: Multilingual Use of Twitter
- Vincent Kuyatt (Undergraduate Student, Computer Science)
Spring 2011

Research Topic: Real time strategy games for social strategy analysis

- Michon Edmonson (Undergraduate Student, Computer Science)
Spring 2011
Research Topic: Computing personality and trust
- Wendy Mock (Undergraduate Student, Computer Science)
Spring 2011
Research Topic: Social tagging of images
- Eric Norris (Undergraduate Student, Computer Science)
Summer 2010
Research Topic: processing social network data
- Nima Rad (Undergraduate Student, Computer Science)
Summer 2010 – Winter 2011
Research Topic: Games for understanding social strategies
- Karen Turner (Undergraduate Student, Psychology)
Spring 2010 – Fall 2010
Research topic: Use of Facebook
- Anthony Rogers (Undergraduate Student, Individual Studies)
Spring 2008
Research topic: Social networks on the web
- Stuart Moore (Undergraduate Student)
Spring 2008, In the context of INFM 220
Research topic: Expert search
- Joanne Kim (Undergraduate Student)
Spring 2008, In the context of INFM 220
Research topic: Expert search
- Mariya Filippova (Undergraduate Student, Computer Science)
Fall 2007 – Spring 2008
Research topic: Social Applications in Facebook
- Greg Phillips (Undergraduate Student, Computer Science)
Spring 2008, In the context of INFM 220
Research topic: Sentiment analysis in online communities
- Matthew Rothstein (Undergraduate Student, Computer Science)
Spring 2007 – Summer 2008
Research topic: Merging social networks on the Semantic Web with FOAF
- Michael Wasser (Undergraduate Student, Computer Science)
Fall 2005 – Spring 2007
Research topic: Adding social context to web pages

3.F.ii Master's**Master's Thesis Committees**

- Committee Member, Thesis Committee
Joshua Watt, Spring 2023
University of Adelaide
- Chair, Thesis Committee
Olivia Garahan , Fall 2017-Spring 2018
- Chair, Thesis Committee
Siddharth Bhagwan , Fall 2017-Spring 2018
- Chair, Thesis Committee
Chiun-Yao Chang , Fall 2017-Spring 2018
- Chair, Thesis Committee
Rebecca Stone , Fall 2017-Spring 2018
- Chair, Thesis Committee
Josh Chang , Fall 2011-Spring 2012
- Chair, Thesis Committee
Rebecca Stone , Fall 2011-Spring 2012
- Chair, Thesis Committee
Siddhartha Bhagwan, Fall 2011-Spring 2012
- Chair, Thesis Committee
Rajan Zachariah, Fall 2011-Spring 2012
- Chair, Thesis Committee
Aria Ghanaat , Fall 2011-Spring 2012
- Member, Thesis Committee
Kelly Hoffman (MLS student, the iSchool): Fall 2007 – Spring 2008
- Member, Thesis Committee
Chris Zamerelli (MLS student, the iSchool): Fall 2007 – Spring 2008
- Member, Thesis Committee
D. Adam Anderson (MLS student, the iSchool): Fall 2007 – Spring 2008

Other

- Zahra Ashktorab (HCIM Student, the iSchool)
Fall 2011 – Spring 2013
- Beth Emmerling (PhD student, the iSchool)
Spring 2010 – Fall 2011
- Cristina Robles (MLS student, the iSchool)
Spring 2010 – Spring 2011
- Alon Motro (MIM student, the iSchool)
Spring 2009 – Spring 2012
- Jeanne Kramer-Smyth (MLS student, the iSchool)
Fall 2008 – Spring 2009

- Rishabh Vyas (MIM student, the iSchool)
Fall 2008 – Spring 2009
- Manasee Mahajan (MIM student, the iSchool)
Fall 2007 – Fall 2008

3.F.iii Doctoral

As Advisor/Co-Advisor

- Advisor, Zahra Ashktorab (Ph.D. Student, iSchool)
Graduated Spring 2018
- Advisor, Cody Buntain (Ph.D. Student, Computer Science)
Graduated August 2017
- Advisor, Irene Eleta (Ph.D. Student, iSchool)
Graduated May 2013
- Advisor, Jes Koepfler (Ph.D. Student, iSchool) 2011-2012
- Co-Advisor with Don Perlis, Hamid Shahri (Ph.D Student, Computer Science)
Graduated Spring 2011
First permanent position: Technology Researcher at the Mayo Clinic
- Co-Advisor with Jim Hendler, Vladimir Kolovski (Ph.D. Student, Computer Science)
Graduated May 2008
First permanent position: Research Scientist, Oracle (Nashua, NH)
- Advisor, John Kleint (Ph.D. Student, Computer Science) 2008
- Co-Advisor with Jim Hendler, Christian Halaschek-Weiner (Ph.D. Student, Computer Science)
Graduated December 2007
First permanent position: Chief Technology Officer of Clados Management LLC.

Member of Dissertation Committees

- Liesl Kraus (Engineering Education, Purdue University), 2022
- Xiaoyun Huang (Information Studies), 2022
- Gareth T. Williams (Communications), 2022
- Hazel Feigenblatt Rojas (Journalism), 2022
- Andrew Otis (Journalism), 2021
- Marina Cascaes Cardoso (Information Studies), 2021
- Rock Stevens (Computer Science), 2020
- Cody Hyman (Accounting), 2020
- John McGahagan (Electrical and Computer Engineering), 2019
- Joseph Meyer (American Studies), 2019
- Faez Ahmed (Mechanical Engineering), 2019
- Margaret Gratian (Mechanical Engineering), 2019
- Abigail Bickford (Public Health), 2018
- Kristopher Micinski (Computer Science), 2017
- Tak Lee (Computer Science), 2017
- Srijan Kumar (Computer Science), 2017
- Kimberley Glasgow (Information Studies), 2017

- Arti Ramesh (Computer Science), 2016
- Jorge Mejia (Business), 2016
- Matthew Lincoln (Art History), 2016
- Peixin Gao (Electrical and Computer Engineering) 2016
- Ning Gao (Information Studies), 2015
- Chanhun Kang (Computer Science), 2015
- Ed Condon (Computer Engineering), 2015
- Jared Sylvester (Computer Science), 2014
- Megan Monroe (Computer Science), 2014
- Kan Leung Cheng (Computer Science), 2013
- Greg Walsh (Information Studies), 2012
- Bo Han (Computer Science), 2012
- Tom Dubois (Computer Science), 2011
- Elena Zheleva (Computer Science), 2011
- Hamid Shahri (Computer Science), 2011
- Chuk-Yang Seng (Computer Science), 2009
- Adam Perer (Computer Science), 2008

Other⁶

- Dana Rotman (Ph.D. Student, the iSchool): Fall 2009
Research Topic: Community structure in YouTube
- Tom DuBois (Ph.D. student, Computer Science): Spring 2009 – Spring 2011
Research Topic: Computing trust in social networks
- Justin Grimes (Ph.D. Student, the iSchool): Spring 2009
Research Topic: Twitter Usage in Congress
- Elena Zheleva (Ph.D. Student, Computer Science): Fall 2008 – Spring 2011
Research Topic: Link prediction in social networks
- Christina Pikas (Ph.D. Student, the iSchool): Spring 2008
Research Topic: Social networks in science blogs
- Philip Fei Wu (Ph.D. Student, the iSchool), Fall 2007 – Spring 2008
Research Topic: Community Response Grids

4 Service

4.A Professional

4.A.i Offices and committee memberships held in professional organizations⁷

- World Wide Web Consortium Semantic Web Best Practices Working Group, March 2004 – October 2004

4.A.ii Reviewing activities for agencies

- Reviewer, NSF Hazards SEES Program, 2015

⁶ Students with whom I have had significant research interaction on specific projects, in a capacity other than their advisor/co-advisor.

⁷ Position on journal board, chairship/membership on conference program committees, and related reviewing activities already reported in Section 2.K are not repeated here.

- Review Panelist, NSF Secure and Trustworthy Computing, Spring 2013
- Review Panelist, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Spring 2013
- Review panelist, NASA Postdoctoral Fellows program Summer 2011
- Review panelist, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Spring 2011
- Review panelist, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Spring 2010
- Review panelist, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Fall 2009
- Review panelist, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Fall 2008
- Outside Reviewer, National Science Foundation (NSF), Directorate for Computer and Information Science and Engineering (CISE), Fall 2007

4.A.iii Other unpaid services to local, state, and federal agencies

- Production of video campaign and social media contest for Department of Defense anti-obesity initiative, in conjunction with Deputy Assistant Secretary of Defense for Health Affairs Summer 2012

4.B Campus

4.B.i College⁸

- Chair, APT Committee (August 2018 - present)
- Chair, Search Committee (2018-2019, 2020-2021, 2022-2023)
- Data Challenge, Mentor 2023, Judge 2022
- Interim Director, PhD Program (July 2017-August 2018)
- Program Director, HCI Masters Program (Summer 2012 – Spring 2014)
- Director, Human-Computer Interaction Lab (Spring 2011 – Spring 2014)
- Member, HCI Masters Committee (Fall 2009 – Spring 2012)
- Member, iSchool Search Committee (Fall 2011– Spring 2012)
- Chair, iSchool Student Awards Committee (Fall 2011 – Spring 2012)
- Co-Director, HCIL (Spring 2009 – Spring 2011)
- Chair, iSchool Undergraduate Committee (Fall 2010 – Spring 2011)
- Member, iSchool Search Committee (Fall 2010 – Spring 2011)
- Member, iSchool Search Committee (Fall 2009 – Spring 2011)
- Member, iSchool ad hoc Research Committee (Fall 2009 – Spring 2011)
- Member, iSchool Undergraduate Committee (Fall 2008 – Spring 2009)
- Assistant Director, Center for Information Policy and E-Government (Fall 2007 – Spring 2010)
- Member, iSchool Doctoral Committee (Fall 2007 – Spring 2010)
- Secretary, College Assembly (Fall 2008 – Spring 2009)

4.C University

- Campus APT (Fall 2023-Spring 2024)

⁸ Membership on dissertation/examination committees are listed in Section 3.F.iii and not duplicated here.

- University Standing Committee on Sexual Assault (Spring 2017 - present)
- ADVANCE Professor (Fall 2016 – 2019)
- Campus reviewer, NSF Partnerships for Innovation Program 2015, 2016
- Member, University of Maryland Provost Search Committee (Fall 2011 – Spring 2012)